Health and Human Capital Effects of Mandated Dependent Insurance Coverage

By

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To my family and especially to two of the strongest women in my life, my mother and my grandmother (1926-2016).

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Chapter 1

Introduction

Increasing insurance coverage among U.S. citizens has been an important goal of recent healthcare reform. Young adults, who have a high rate of uninsurance, are a group often targeted by policymakers. Policymakers have largely used dependent mandates, which allow young adults to stay on their parent's or guardian's insurance plan, to raise the insurance rate of young adults. In this dissertation I compile an original set of state dependent mandates, use them to better understand the impact of the recent Affordable Care Act (ACA) dependent mandate and evaluate their impact.

In the second chapter, I provide new evidence on the effects of state dependent mandates and the ACA dependent mandate. Using a more extensive set of state laws than prior works, data from the Consumer Population Survey (CPS), data from the CPS Annual Social and Economic Supplement (CPS ASEC), data from the American Community Survey (ACS) and a longer time period I estimate the effects of dependent mandates. Compared to prior studies, I find that state mandates resulted in a larger and more robust increase in insurance coverage. I find that the ACA dependent mandate is robust to controls for pre-existing state policies. I find heterogeneous effects by sex with males having larger coverage gains. Despite the gains in insurance, I find no effect on self-rated health. Looking at labor market outcomes, I find evidence of increased entrepreneurship, some evidence of a decrease in average weekly hours, mixed evidence of changes in unemployment duration and no effect on labor force participation. Looking at education, I find an increased likelihood of having a bachelor's degree and of taking some college courses. I further investigate how dependent mandates affect parents' decisions and find that state dependent mandates have no effect on the heads of households' labor supply or overall insurance coverage, though there is evidence that, among parents with employer sponsored insurance, those with eligible children are more likely to switch to an employer sponsored family plan and this effect is much larger for households with only one parent present. Among employer sponsored insurance policyholders I find no evidence of shifting costs through decreased wages. However, I do find evidence that some employers reduce costs by no longer paying premiums on insurance plans.

In the third chapter, I study the effect of state dependent mandates on the use of inpatient care. Using the Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality, I find dependent mandates led to an increased likelihood of young adults paying with some form of insurance, largely private, instead of self-pay. I also find evidence of an increase in the intensity of care provided as I find increases in the length of stay, number of procedures performed and total charges. I find that young adults are more likely to have a visit for mental health care following a mandate going into effect. Overall I find results consistent with an insurance gain and increased utilization as is expected with a lower cost of care from a gain in insurance.

In the fourth chapter, I study how the ACA dependent mandate affected Human Immunodeficiency Virus (HIV) testing among young adults. Using the Behavioral Risk Factor Surveillance System (BRFSS) I find that the ACA dependent mandate increased the likelihood of young adults ever having an HIV test. I also find that young adults most recent test location changes following the dependent mandate. Young adults are more likely to be tested at a hospital and less likely to be tested at clinics. Overall, the findings provide evidence that the ACA dependent mandate has had an impact on preventive care in the form of HIV testing.

This dissertation provides empirical evidence that dependent mandates affect both health and non-health outcomes for dependents, affect parents of dependents and policyholders of employer sponsored group insurance plans. These results show that the gains from dependent are more than just an increase in insurance coverage: there is an increase in utilization, education and screening procedures. Broadly speaking, gains were larger for males who on average have lower a lower insurance coverage rate and utilization than females. These findings provide information useful for policymakers in understanding the direct effects of dependent mandates and the potentially wide reaching indirect effects of dependent mandates that may persist leading to later-in-life gains.

Chapter 2

New Evidence on the Effects of Dependent Coverage Mandates

2.1 Introduction

Insurance mandates have been an important tool used by policy makers to shape the private insurance and health care landscape. Mandates are generally used in three ways. The first way mandates are used is to require private insurance plans to cover certain benefits such as specific services or procedures. The second way mandates are used is to require private insurance plans to cover the services of certain types of health care providers. The third way mandates are used is to require private insurance plans to cover certain types of individuals. From a policy point of view, mandates can be used to address perceived shortcomings in insurance coverage, services, or in specific groups who are under-insured or uninsured. A mandate that has received considerable attention in both the news and research has been the Patient Protection and Affordable Care Act's (PPACA or ACA) dependent mandate. This federal mandate targets young adults—a population with a high rate of uninsurance of around 30 percent through the 1990s and 2000s. States have issued several dependent mandates beginning as early as 1982 aiming to decrease the uninsurance rate among young adults.

The use of mandates is not without cost. The government may use mandates as a means to increase coverage for the electorate without having to fund the costs, forcing the bill to be paid by others. Mandating the content of an insurance plan will naturally tend to make the plan more expensive unless the mandated provisions were already voluntarily covered. Gabel and Jensen (1989) and Jensen and Gabel (1992) find that insurance mandates raise the price of health insurance, lead to more firms self-insuring and cause some small firms to not offer health insurance that otherwise would have. Additionally, Gruber (1994) and Goda et al. (2016) find that mandated benefits lead to wage reductions. Rather than focusing on the cost of dependent mandates, I aim to better understand the effect of dependent mandates by using original legal data I compiled on the timing and content of state dependent mandates.

First, I estimate the impact of dependent mandates on insurance coverage. I begin by examining state dependent mandates using both my coding of legislative changes and the codings used in previous analyses. I find that including laws passed prior to the 2000s makes a large difference in the significance and magnitude of prior estimates. Taking advantage of a longer time period that captures more variation—the initial passage of laws mandating coverage and subsequent amendments to the laws—I find a large gain in insurance coverage among the targeted population occurring largely through employer sponsored insurance plans. Next, I proceed by investigating the effect of the ACA dependent mandate. I incorporate my legal data on state dependent mandates by controlling for individuals previously eligible and excluding states that provide treatment to individuals traditionally used as a control in the ACA dependent mandate literature. With these additional controls and omissions, I still find a large gain in insurance coverage from the ACA dependent mandate that is consistent with prior studies.

Second, I estimate the impact of dependent mandates on labor market outcomes. I find that state dependent mandates result in increased educational attainment, increased entrepreneurship and increased unemployment duration. Turning to the ACA dependent mandate I find an increased likelihood in living with at least one parent and a decrease in weekly hours. I find some evidence that females are more likely to be unemployed and males have a reduction in unemployment duration.

This chapter proceeds as follows: In section 2.2, I provide information on the background of dependent mandates and existing evidence on the effect of dependent mandates. In section 2.3, I describe the data used in my analyses and outline my empirical strategy. In section 2.4, I present the empirical results and in section 2.5, I conclude.

2.2 Background

In this section, I cover background information relevant to my analysis. First, I provide a summary on the institutional background of dependent mandates both at the state level and federal level. Second, I discuss previous findings on the effects of dependent mandates and test the results for sensitivity to legal coding.

2.2.1 Institutional Background

States have been using dependent mandates to extend eligibility to legally defined dependents as early as 1982. State dependent mandates primarily define dependency status using age, marital status, and student status or residency status. Some additional definitions require that an individual not have dependents of their own and/or that dependents may not be eligible for other health insurance plans.

Table 2.1: Summary of State Mandates by Decade

	1980	1990	2000	2010
Eligibility requirements†				
Must be unmarried		3	15	29
Must be a student		4	13	13
Must not have dependents				5
Must not be eligible for other plans				4
Limiting age				
21				
22		3	10	5
23		1	2	4
24		1	4	13
25			1	6
26			1	1
27				1
28				1
29				3
30				1
Number of states with mandates		5	18	35

Notes: For each count, the number reported is the number of mandates that are effective as of January 1st during that decade. The limiting age is the highest age one may be and still be eligible as a dependent. All information is based on my interpretation of information gathered from WestLaw Next and Lexis Nexis.

† The eligibility requirements are not mutually exclusive. For example, a state defining dependents as unmarried students would be counted under both the "Must be unmarried" total and the "Must be a student" total.

Table 2.1 reports the limiting ages, eligibility requirements and number of states with mandates by decade. States have tended to adopt more lenient age requirements over time, moving from the highest eligible age being twenty four on January 1, 1990, to the highest being thirty on January 1, 2010. On January 1, 2010, Thirty five states had mandates in place with twenty nine of those requiring the dependent to be unmarried, thirteen requiring the dependent to be a student, five requiring the dependent to claim no dependents of their own and four requiring the dependent to not be eligible for other insurance plans. Between 1990 and 2010, thirty states introduced mandates and when including marginal changes in states with mandates already in place, there are over fifty changes in policies during this period.

Despite the large number of states extending dependency status, these mandates are not binding for all firms. The 1974 Employee Retirement Income Security Act (ERISA) places self-insured employers under federal jurisdiction, meaning that state mandates do not apply to self-insured firms. In 2008, 55 percent of workers with health insurance were covered by a self-insured firm and 89 percent of workers in a firm with 5,000 or more employees were covered by a self-insured firm (Employee Benefit Research Institute, 2009). Consequently, the estimates of state mandates should have less of an impact than federally binding dependent mandates.

The passage of the Patient Protection and Affordable Care Act raised the federal age limit for dependent status from eighteen to twenty five for insurance coverage. The ACA dependent mandate extended coverage regardless of marital status starting on September 23, 2010. The ACA dependent mandate was one of the earliest parts of the PPACA to go into effect and has had a sizable impact as over 3 million young adults have been able to stay on their parents' plans (Obama Care Facts). With the ACA dependent mandate being federal law, self-insured firms now must cover dependents up to age twenty five. It is reasonable to expect that any estimates of the ACA dependent mandate's effect on insurance coverage should be considerably larger than estimates of state dependent mandates' effects.

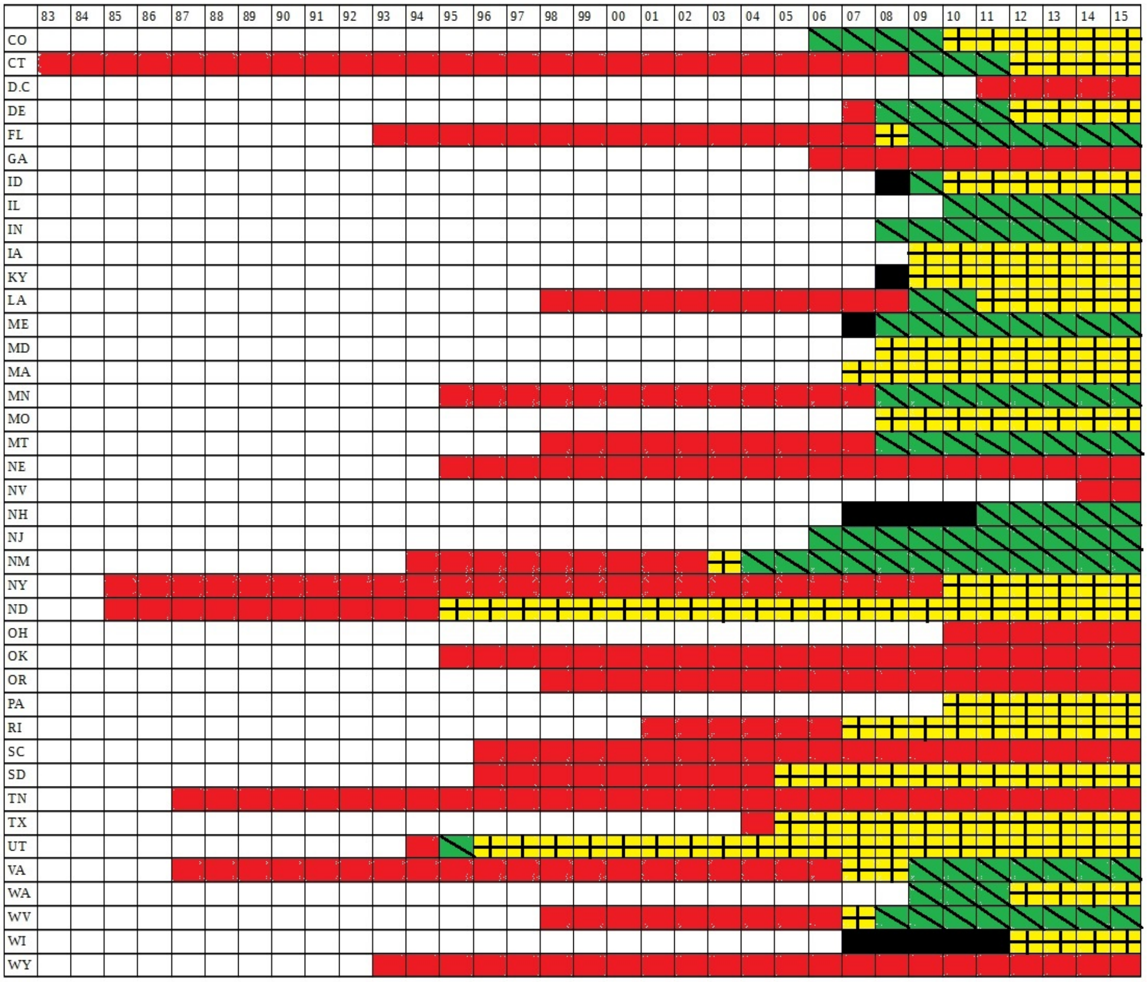
2.2.2 Existing Evidence and Sensitivity to Legal Codings

Four studies examine state dependent mandates, however, none of these studies has taken full advantage of the variation in laws implemented and amended prior to the 2000s. Levine et al.

(2011) find an increase of insurance coverage among targeted individuals of about 2 to 4 percentage points. Monheit et al. (2011) find an increase of about 1.5 to 4 percentage points for dependents living with parents. Depew (2015) finds an increase in dependent coverage of about 2 percentage points using only age eligibility requirements and an increase of about 5 to 7 percentage points using all eligibility requirements. In response to Levine et al. (2011) and Monheit et al. (2011), Burgdorf (2014) argues that the increases in coverage from dependent mandates are largely due to changes in spousal coverage. Monheit et al. (2015) respond by arguing that changes in spousal coverage are not a reasonable channel through which a parental dependent mandate should work, that many state dependent mandates only apply to unmarried young adults and that some Consumer Population Survey (CPS) editing procedures may be adding to the noise of questions on the source of coverage. Dillender (2014) finds that dependent mandates increased wages later in life among those who were eligible for dependent coverage during their early twenties and suggests that it may be due to health insurance lowering the cost of college, reducing job lock or by accepting a higher paying job with no benefits.

Despite the agreement among these four studies on the impact of state dependent mandates on young adults, when comparing the laws used in prior studies to those that I have gathered, I find considerable differences. The four studies rely primarily on the National Conference of State Legislatures (NCSL). The NCSL tracks current bills and laws for various topics. The earliest report on dependent mandates available on their website was released in 2009. NCSL is forward looking in the sense that they document the laws currently on the books, track bills that are proposed and periodically update their information as laws are passed. NCSL does not necessarily search for laws in place prior to the start of when they began tracking a topic. In taking the NCSL information at face it would treat some marginal changes to existing laws as the implementation of a law. Figure 2.1 illustrates how the use of NCSL would omit many relevant laws in effect prior to 2009.

Figure 2.1: Comparing NCSL 2009 to my Coding of Legal Data



Notes: Each cell represents a state-year observation. Red cells represent where NCSL 2009 does not have a law that my legal data does, green cells with a slash represent where NCSL 2009 and my legal data are in agreement, yellow cells with a cross represent where NCSL 2009 and my legal data both have laws but the eligibility requirements differ, and black cells represent where NCSL 2009 has a law in effect that my legal data does not. NCSL 2009 is used for this figure; a newer version of NCSL would result in more accurate cells for the years after 2009.

It is important to see if the coding of laws makes a difference. I find that using the NCSL 2009 coding and my coding for the 2001-2009 period makes a large difference in the estimated effects. Following Levine et al. (2011), the estimating equation for the differences-in-differences

(DD) model is:

$$y_{iast} = \alpha + \beta Post_{st} + \gamma X_{iast} + \delta_s + \zeta_a + \nu_t + \theta unemp_{st} + \varepsilon_{iast} \quad (2.1)$$

$Post_{st}$ takes a value of one if a law is in place in state s at time t. X_{iast} includes controls for sex, marital status, student status, living with a parent and household income as a percent of the federal poverty line. Also included are state-year unemployment rates, year fixed effects, age fixed effects and state fixed effects. The analysis is done on two samples, the full sample of young adults aged 19 to 24 and the eligible sample of young adults aged 19 to 24. The eligible sample is defined by the policy codings' eligibility requirements for states with mandates and, for states with no mandates, unmarried individuals are included. An additional differences-in-differences-in-differences (DDD) estimate is performed using state mandate eligibility requirements as the third difference.

In Table 2.2, I report the estimates on the likelihood of having any insurance using the NCSL codings for the 2001-2009 time period and the estimates using my codings over both the 2001-2009 time period and the 1996-2009 time period.

Table 2.2: Likelihood of Any Insurance Coverage by Legal Coding

	NCSL Codings	My Codings	
CPS Variables	2001-2009	2001-2009	1996-2009
DD, Full sample	-0.003	-0.023***	-0.020***
	(0.008)	(0.008)	(0.007)
DD, Eligible sample	0.004	-0.020**	-0.016*
	(0.013)	(0.018)	(0.013)
DDD, Full sample	0.039***	0.015	0.019
	(0.013)	(0.018)	(0.013)
DD, Non-student sample	-0.004	-0.020*	-0.019**
	(0.009)	(0.011)	(0.009)
DD, Eligible non-student sample	0.012	-0.010	-0.007
	(0.009)	(0.012)	(0.011)
DDD, Non-student sample	0.058***	0.028	0.031*
	(0.019)	(0.018)	(0.016)

Notes: The data used is the CPS ASEC.Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively. The full sample size for the years 2001-2009 is 132,689 and for the years 1996-2009 is 180,589. The eligible sample size for the years 2001-2009 is 105,669 and for the years 1996-2009 is 142,443. The non-student sample size for the years 2001-2009 is 81,437 and for the years 1996-2009 is 112,079. The eligible non-student sample size for the years 2001-2009 is 57,721 and for the years 1996-2009 is 78,491.

Looking at the likelihood of having any insurance, the full sample DDD estimate under NCSL 2009 finds a significant 3.9 percentage point increase, while under my coding it loses significance, decreases in magnitude and changes sign. Similarly, the non-student sample DDD estimate finds a significant 5.8 percentage point increase, while under my coding, it loses significance and decreases in magnitude. When I extend the period of analysis and use my legal coding, the non-student sample DDD results in a significant increase of 3.1 percentage points.

In Table 2.3, I report the estimates on the likelihood of having public insurance using the NCSL codings for the 2001-2009 time period and then the estimates using my codings over both the 2001-2009 time period and the 1996-2009 time period.

Table 2.3: Likelihood of Public Insurance Coverage by Legal Coding

	NCSL Codings	My Codings	
CPS Variables	2001-2009	2001-2009	1995-2009
DD, Full sample	-0.012*	-0.011	-0.012
	(0.006)	(0.007)	(0.008)
DD, Eligible sample	-0.010*	-0.010*	-0.011*
	(0.005)	(0.006)	(0.007)
DDD, Full sample	0.009	0.007	0.008
	(0.012)	(0.018)	(0.013)
DD, Non-student sample	-0.012	-0.008	-0.010
	(0.009)	(0.010)	(0.011)
DD, Eligible non-student sample	-0.009	-0.004	-0.007
	(0.008)	(0.009)	(0.011)
DDD, Non-student sample	0.011*	0.014	0.020
	(0.009)	(0.014)	(0.019)

Notes: The data used was the CPS ASEC. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively. The full sample size for the years 2001-2009 is 132,689 and for the years 1996-2009 is 180,589. The eligible sample size for the years 2001-2009 is 105,669 and for the years 1996-2009 is 142,443. The non-student sample size for the years 2001-2009 is 81,437 and for the years 1996-2009 is 112,079. The eligible non-student sample size for the years 2001-2009 is 57,721 and for the years 1996-2009 is 78,491.

Looking at the likelihood of having public insurance, the full sample DD estimate under NCSL

2009 finds a significant 1.2 percentage point decrease, while under my coding it loses significance. The eligible sample DD estimate has roughly a 1.0 percentage point decrease that is significant using both codings. The result holds when the time period is extending back to 1995. The non-student sample DDD estimate under NCSL 2009 finds a significant 1.1 percentage point increase which increases in magnitude and is not significant under my coding.

In Table 2.4, I report the estimates on the likelihood of having private insurance using the NCSL codings for the 2001-2009 time period and then the estimates using my codings over both the 2001-2009 time period and the 1996-2009 time period.

Table 2.4: Likelihood of Private Insurance Coverage by Legal Coding

	NCSL Codings	My Codings	
CPS Variables	2001-2009	2001-2009	1995-2009
DD, Full sample	0.009	-0.010	-0.011
	(0.006)	(0.008)	(0.008)
DD, Eligible sample	0.017**	-0.007*	-0.005
	(0.006)	(0.009)	(0.008)
DDD, Full sample	0.037***	0.013	0.017
	(0.010)	(0.020)	(0.015)
DD, Non-student sample	0.008	-0.010	-0.011
	(0.008)	(0.014)	(0.013)
DD, Eligible non-student sample	0.024**	-0.001	-0.000
	(0.010)	(0.014)	(0.015)
DDD, Non-student sample	0.056***	0.021	0.025
	(0.018)	(0.013)	(0.015)

Notes: The data used was the CPS ASEC. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively. The full sample size for the years 2001-2009 is 132,689 and for the years 1996-2009 is 180,589. The eligible sample size for the years 2001-2009 is 105,669 and for the years 1996-2009 is 142,443. The non-student sample size for the years 2001-2009 is 81,437 and for the years 1996-2009 is 112,079. The eligible non-student sample size for the years 2001-2009 is 57,721 and for the years 1996-2009 is 78,491.

Looking at the likelihood of having private insurance, the eligible sample DD estimate under NCSL 2009 finds a significant 1.7 percentage point increase. Under my coding the estimate is a significant decrease of 0.7 percentage points. The eligible sample DD under NCSL 2009 finds a 3.7 percentage point increase which decreases in magnitude and loses significance under my coding. The eligible non-student sample DD estimate under NCSL 2009 finds a 2.4 percentage point increase which loses significance and changes sign when using my coding. The non-student sample DDD estimate finds a 5.6 percentage point increase which loses significance and decreases in magnitude under my coding. These results show that the coding of the laws makes a difference on the mandates' estimated effects.

A large number of works examine the ACA dependent mandate but only a handful take advantage of pre-existing state dependent mandates. These works take advantage of the age eligibility cutoff using a difference-in-difference model comparing those younger than twenty six to those older than twenty six before and after the ACA dependent mandate went into effect. Slusky (2015) demonstrates that many positive significant results occur for placebo policy implementation dates, suggesting that the effect of the ACA's dependent mandate may have been overstated in the DD framework. In a DD analysis, it is important to check that the parallel trends assumption holds and the result is not driven by changes occurring prior to the ACA dependent mandate going into effect. The ACA dependent mandate has resulted in a well-documented increase in insurance coverage among dependents.[1] Following the ACA dependent mandate going into effect, young adults were more likely to have dependent coverage, less likely to have an employer sponsored plan in their own name and less likely to have individually purchased their own insurance.[2] Barbaresco et al. (2015) find an increase in the likelihood of reporting excellent health among young adults targeted by the ACA dependent mandate.

Additionally, several papers have examined the ACA dependent mandate's impact on non-health outcomes. Antwi et al. (2013) find evidence that young adults were less likely to work full time and worked fewer hours. However, Heim et al. (2015)find no evidence of labor changes in tax data. Colman and Dave (2015) find that the ACA dependent mandate reduced job lock among young adults but Bailey and Chorniy (2016) find no evidence of job lock decreasing. Looking at marriage, Abramowitz (2015) finds that dependents are less likely to get married and more likely to get divorced following the reform.

[1] Gains in insurance are documented by Cantor et al. (2012a), Antwi et al. (2013), Mulcahy et al. (2013a), Sommers and Kronick (2012a), Antwi et al. (2015), Saloner et al. (2015) and Barbaresco et al. (2015).

[2] These effects on type of coverage are found in Cantor et al. (2012a) and Antwi et al. (2013).

2.3 Data and Empirical Strategy

In this section, I describe each dataset below and outline my empirical strategy. My analysis uses three datasets. For my analyses of state dependent mandates, I use the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) and the Current Population Survey (CPS). For study of the ACA dependent mandate, I use the American Community Survey (ACS) and the CPS.

2.3.1 Data

Each of the three datasets contains state and time information allowing me to merge the datasets with my policy codings. Additionally, each dataset contains basic individual demographic characteristics such as age, race, ethnicity, marital status, student status,[3] and educational attainment.

2.3.1.1 CPS ASEC

The CPS ASEC is useful for my analysis because it is an annual state representative survey administered primarily in March and includes questions about the past year's insurance outcomes extending back to the late 1980s. The CPS ASEC samples range in size from about 63,000 to 100,000 households comprised of roughly 130,000 to 218,000 individuals. Sampled individuals are fifteen years of age or older and are not in the armed forces, prisons, long-term care hospitals, nursing homes or other such institutions. The majority of household responses are answered by one individual—the reference person—who is the (or one of the) owner(s) or renter(s) of the housing unit. Family interrelationships are identified in the data, allowing me to look at family outcomes in addition to individual outcomes.

Prior works have used the insurance coverage outcomes provided in the CPS ASEC, however, these outcomes have significant problems that I deal with by using the State Health Access Data Assistance Center (SHADAC) enhanced variables. It is important to note that data editing

[3] In the CPS from 1986 to 2012, student status is asked of persons aged 16 to 24. Beginning in 2013, the ages were extended up to and including 24.

procedures used from 1997 to 2006 produced a systematic error causing family members to be erroneously coded as uninsured when the family's respondent had employer sponsored insurance (ESI) or purchased insurance, and reported that this insurance plan covered all other family members. When the error was recognized, the 2005 and 2006 CPS ASEC data were reprocessed and corrected versions were released. The years 1997-2004 were not corrected but flags were released that can be used to update the data. Additionally, since the introduction of health insurance coverage questions the survey underwent reweighting in 1994 and 2003.[4] Since 1988, SHADAC has provided enhanced variables and weights that account for methodological changes and problems in the CPS ASEC insurance coverage outcomes. Starting in 1996, CPS ASEC and, consequently, SHADAC added the outcomes of ESI or individually purchased insurance coverage.

2.3.1.2 CPS

The CPS is useful for analyzing labor market outcomes because it includes state representative monthly data. The CPS samples consist of roughly 60,000 to 70,000 households each month. Unlike the CPS ASEC, the CPS refers to activities in the prior week rather than the last calendar year. The individuals targeted for sampling are the drawn from the same population as those in the CPS ASEC. The CPS contains detailed questions on labor force participation, employment and other labor market outcomes.

2.3.1.3 ACS

The ACS is useful for my analysis because it includes data on both health insurance coverage and labor market outcomes from the 2000s to present. The ACS is a large representative dataset, which is conducted by contacting about 3.5 million households annually. The ACS selects a random sample of just under 300,000 addresses (rather than specific individuals) each month. In an attempt to reduce non-responses, when an individual does not respond to the initial survey request,

[4] See SHADAC issue brief 19 for a more complete list of methodological changes (State Health Access Data Assistance Center. 2009).

a follow up phone call is given. In the event that neither method of contact works or the household refuses to participate, a personal interview may be attempted.

2.3.2 Identification Strategy

2.3.2.1 State Dependent Mandates

I employ a differences-in-differences-in-differences (DDD) model using my policy codings to exploit the variation in state (first difference), timing (second difference) and eligibility requirements (third difference) of state dependent mandates. To justify this as a viable strategy, I look for evidence of selection into eligibility and estimate a time-to-adopt model.

To look for selection into eligibility, I employ a differences-in-differences model using variation in state (first difference) and timing (second difference) of policy adoption to predict the likelihood of being a student or unmarried. The estimating equation for outcome y_{iast} for an individual i age a living in state s at time t is:

$$y_{iast} = \alpha + \beta(Post_{st}) + \gamma x_i + \delta_s + \nu_t + \varepsilon_{iast} \quad (2.2)$$

The coefficient of interest is β. $Post_{st}$ is an indicator taking a value of one in state s if a dependent coverage policy is in place at time t. x_i contains individual controls for sex, education, age, and race/ethnicity. δ_s and ν_t are fixed effects for state and time. In Table 2.5 I present the results and find no evidence of selection into being a student or unmarried.

Table 2.5: DD Estimates of State Mandates' Effect on the Likelihood of Being a Student or Unmarried

	All	Male	Female
Student	0.0039	-0.0011	0.0097
	(0.0219)	(0.0237)	(0.0307)
Unmarried	0.0133	0.0056	0.0169
	(0.0161)	(0.0165)	(0.0175)
Sample size	189,854	92,688	97,166

Notes: The data used was the CPS ASEC from 1996-2010. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

Second, I estimate a Cox duration model on the timing of policy adoption and present the results in Table 2.6. An advantage of using a Cox duration model is that the form of the baseline hazard rate is determined by the data rather than being specified as in other duration model approaches. The hazard rate estimated is of the form

$$h_i(t) = h_0(t) exp(\beta x). \tag{2.3}$$

The baseline hazard function is given by $h_0(t)$ and x is a set of covariates. I treat the adoption of a state dependent mandate as the event of interest[5] and include covariates at the state year level for the number of hospital beds, number of uninsured individuals, total health expenditure, number of individuals in poverty, the unemployment rate, state GDP, population, percent aged fifteen to twenty four, percent black, if the state has a democratic governor and the democratic presidential vote tally. I find no evidence of selection into eligibility or strong predictors of the timing of policy adoption.

[5] I use the Efron method for handling ties.

Table 2.6: Duration Analysis on Time to Adopt

	Hazard Ratio	Standard Error
Number of hospital beds in ten thousands	2.2906	6.2216
Number of uninsured in ten thousands	1.1006	0.0692
Total health expenditure in one hundred millions	1.0227	0.0230
Number in poverty in ten thousands	0.9389	0.0556
Unemployment rate	0.8627	0.3386
State GDP in billions	0.9652	0.0322
Population in millions	0.2496	0.6052
Percent aged 15 to 24	0.9763	0.0428
Percent black	0.9982	0.0048
Democratic governor	0.9863	0.8562
Democratic presidential vote tally in ten thousands	1.0272	0.0417

Notes: The data used was the State Health Policy Research Dataset (SHEPRD): 1980-2010. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

I begin by estimating the following equation, where i indexes an individual, a indexes an individual's age, s indexes an individual's state, t indexes time, m indexes an individual's marital status, e indexes an individual's student status and y_{iastme} are insurance and health outcomes of interest:

$$\begin{aligned} y_{iastme} = \alpha + \beta(Post_{st} \times Eligible_{astme}) + \gamma x_i + \delta_s + \zeta_a + \nu_t + \theta_{as} + \kappa_{st} \\ + \eta_{ma} + \iota_{ms} + \lambda_{mt} + \mu_{ea} + \pi_{es} + \xi_{et} + \varepsilon_{iastme} \end{aligned} \tag{2.4}$$

The coefficient of interest is β. $Post_{st}$ is an indicator taking a value of one in state s if a dependent coverage policy is in place at time t. $Eligible_{astme}$ is an indicator taking a value of one for individuals satisfying the age, marital and student eligibility requirements in state s at time t. X_i contains individual controls for sex, race and Hispanic origin. δ_s, ζ_a, ν_t, θ_{as}, κ_{st}, η_{ma}, ι_{ms}, λ_{mt},

μ_{ea}, π_{es} and ξ_{et} are fixed effects for state, age, time, age-by-state, age-by-time, and state-by-time, unmarried-by-age, unmarried-by-state, unmarried-by-time, student-by-age, student-by-state and student-by-time fixed effects, respectively.

To analyze labor market outcomes, I exclude states with student eligibility requirements and modify equation 2.4 to become:

$$\begin{aligned} y_{iastm} = \alpha + \beta(Post_{st} \times Eligible_{astm}) + \gamma x_i + \delta_s + \zeta_a + \nu_t + \theta_{as} + \kappa_{st} \\ + \eta_{ma} + \iota_{ms} + \lambda_{mt} + \varepsilon_{iastm} \end{aligned} \tag{2.5}$$

Now $Eligible_{astm}$ is an indicator taking a value of one for individuals satisfying the age and marital eligibility requirements in state s at time t. This estimating equation does not include student-by-age, student-by-state or student-by-time fixed effects but otherwise follows the same definitions as above.

For both analyses I restrict the sample to young adults aged nineteen to twenty four. The CPS and CPS ASEC only ascertains the student status for individuals aged sixteen to twenty four prior to 2013. I restrict my analysis to the contiguous United States and exclude Massachusetts, which underwent a significant health reform in 2006 aiming to provide all residents with access to affordable health insurance.

2.3.2.2 Affordable Care Act Dependent Mandate

I use a differences-in-differences (DD) model using the timing (first difference) and eligibility (second difference) of the ACA dependent mandate. Unlike prior DD analyses, I control for pre-existing state dependent mandates and exclude states with particularly high dependent mandates. I estimate the following equation, where i indexes an individual, a indexes an individual's age, s

indexes an individual's state, t indexes time and y_{iast} are the outcomes of interest:

$$Y_{iast} = \alpha + \beta(Post_t \times Eligible_i) + \theta_{ist} + \gamma x_i + \delta_s + \zeta_a + \nu_t + \varepsilon_{iast} \tag{2.6}$$

The coefficient of interest is β. $Post_t$ is an indicator taking a value of one if the time period is after September 23, 2010 when the ACA dependent mandate went into effect. $Eligible_i$ is an indicator taking a value of one for individuals aged twenty five or less who are eligible under the ACA dependent mandate. θ_{ist} is a dummy variable taking a value of one for individuals who were previously eligible for a state dependent mandate. x_i contains individual controls for sex, race and Hispanic origin. δ_s, ζa and ν_t are fixed effects for state, age and time, respectively.

In my estimations of the ACA dependent mandate's impact, I exclude states with dependent mandates in place that extend beyond age twenty five. Specifically I exclude Washington D.C., Florida, New Jersey, New York, North Dakota, Ohio and Pennsylvania. Many of these states extended coverage close to the timing of the ACA dependent mandate and I exclude them to prevent individuals eligible for a dependent mandate from being in the control group. I also exclude individuals who are twenty six years of age. It is unclear if twenty six year olds are treated or not during the period of reference. I compare 23-25 year olds (the treated group) to 27-29 year olds (the control group).

2.4 Results

I present two sets of results, each containing evidence from state dependent mandates and the ACA dependent mandate. First, I present the effect of dependent mandates on insurance coverage and self-rated health. Second, I examine the impact on labor market outcomes. Additionally, I present a section containing additional analyses exploring my results.

2.4.1 Insurance Coverage

2.4.1.1 State Dependent Mandates

First, I present health insurance coverage means and DDD estimates in Table 2.7, where I find sizable gains in insurance coverage. Roughly 71 percent of young adults are insured, which matches up with prior estimates. For the full sample I find a 4.23 percentage point increase in the likelihood of having any insurance coverage and a 4.56 percentage point increase in the likelihood private insurance which is driven largely by a 5.39 percentage point increase in the likelihood of having ESI. I find no significant change in the likelihood of having public insurance. The results are similar when estimated by sex, with the estimates for the male population having slightly larger magnitudes than those of the female population.

Table 2.7: DDD Estimates of State Mandates' Effect on Insurance Coverage

		DDD Estimates		
	Mean	All	Male	Female
Any insurance	0.7069	0.0423***	0.0447***	0.0407***
	(0.0013)	(0.0090)	(0.0113)	(0.0115)
Private insurance	0.6040	0.0456***	0.0479***	0.0448***
	(0.0014)	(0.0101)	(0.0165)	(0.0135)
Employer sponsored insurance	0.4891	0.0539***	0.0631***	0.0500***
	(0.0014)	(0.0122)	(0.0186)	(0.0135)
Individually purchased insurance	0.0589	0.0037	-0.0020	0.0064
	(0.0007)	(0.0063)	(0.0122)	(0.0080)
Public insurance	0.1344	-0.0038	-0.0087	-0.0015
	(0.0010)	(0.0084)	(0.0144)	(0.0093)
Public insurance, excluding military	0.1038	-0.0042	0.0085	-0.0013
	(0.0009)	(0.0106)	(0.0154)	(0.0110)
Medicare	(0.0068)	-0.0010	-0.0032	0.0004
	(0.0068)	(0.0180)	(0.0021)	(0.0027)
Military insurance	0.0285	(0.0026)	0.0044	0.0004
	(0.0005)	(0.0076)	(0.0097)	(0.0073)
Sample size		170,440	82,954	87,486

Notes: The data used was the CPS ASEC from 1996-2010. All outcomes are using SHADAC enhanced variables and are estimated under the specification in equation (2). Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

Next, I present the self-rated health means and DDD estimates in Table 2.8, where I find no effects. Overall and by sex, none of the estimates are significant. The estimates are small with none exceeding 1 percentage point. The population is already healthy with over 75 percent reporting having at least very good health, and over 95 percent reporting having at least good health.

Table 2.8: DDD Estimates of State Mandates' Effect on Self-rated Health Outcomes

		DDD Estimates		
	Mean	All	Male	Female
Excellent health	0.4200	-0.0057	-0.0057	-0.0068
	(0.0013)	(0.0116)	(0.0148)	(0.0129)
Very good health	0.3329	0.0081	0.0138	0.0053
	(0.0013)	(0.0089)	(0.0134)	(0.0094)
Good health	0.2060	-0.0021	-0.0109	0.0053
	(0.0011)	(0.0069)	(0.0088)	(0.0095)
Fair health	0.0343	-0.0014	0.0012	-0.0038
	(0.0005)	(0.0026)	(0.0041)	(0.0043)
Poor health	0.0069	0.0010	0.0016	-0.0000
	(0.0002)	(0.0017)	(0.0024)	(0.0022)
At least very good health		0.0024	0.0081	-0.0015
		(0.0082)	(0.0095)	(0.0102)
At least good health		0.0003	-0.0028	0.0038
		(0.0038)	(0.0049)	(0.0052)
At least fair health		-0.0010	-0.0016	0.0000
		(0.0017)	(0.0024)	(0.0022)
Sample size		189,854	92,688	97,166

Notes: The data used was the CPS ASEC from 1996-2010. Outcomes are estimated under the specification in equation (2).Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

Lastly, I present the health insurance coverage means and DDD estimates excluding states with student eligibility requirements in Table 2.9, where I find a smaller but still meaningful increase in insurance coverage. The means of insurance coverage for this sample are nearly the same as the full sample. Overall, I find smaller increases in the likelihood of insurance coverage—a 2.33 percentage point increase for any insurance coverage, a 2.92 percentage point increase for private insurance coverage and a 4.89 percentage point increase for ESI. Again, by sex, the magnitudes of estimates are larger for males. The increase in the likelihood of having ESI is significant for both sexes, whereas the increase in likelihood of any insurance is only significant for males.

Table 2.9: DDD Estimates of State Mandates' Effect on Insurance Coverage, Excluding States with Student Requirements

		DDD Estimates		
	Mean	All	Male	Female
Any insurance	0.7103	0.0233**	0.0414*	0.0154
	(0.0015)	(0.0111)	(0.0224)	(0.0124)
Private insurance	0.6099	0.0292**	0.0361	0.0283
	(0.0016)	(0.0113)	(0.0218)	(0.0196)
Employer sponsored insurance	0.4933	0.0489***	0.0577**	0.0450*
	(0.0017)	(0.0164)	(0.0258)	(0.0234)
Public insurance	0.1300	0.0004	0.0033	-0.0019
	(0.0011)	(0.0130)	(0.0198)	(0.0161)
Sample size		115,124	56,119	58,925

Notes: The data used was the CPS ASEC from 1996-2010. All outcomes are using SHADAC enhanced variables and are estimated under the specification in equation (3).Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

2.4.1.2 Affordable Care Act Dependent Mandate

In Table 2.10, I present the DD estimates of the ACA dependent mandate on insurance coverage for the ACS dataset. The type of coverage for this sample is very close to that reported for the CPS ASEC above. About 70 percent have any insurance coverage, with the largest source of insurance being through private ESI plans. In the ACS sample I find a 5.8 percentage point increase in the likelihood of having any insurance coverage. I find a 7.1 percentage point increase in private insurance coverage, which, when broken down by type, is driven by a 8.6 percentage point increase in the likelihood of having ESI and a 1.2 percentage point decrease in the likelihood of having an individually purchased insurance plan. I find about a 1.1 percentage point decrease in the likelihood of having public insurance.

Table 2.10: DD Estimates of the ACA Dependent Mandate, 23 to 29 Year Olds

		DD Estimates		
	Mean	All	Male	Female
Any insurance	0.7022	0.0582***	0.0654***	0.0508***
	(0.0008)	(0.0040)	(0.0047)	(0.0041)
Private insurance	0.5969	0.0706***	0.0747***	0.0663***
	(0.0008)	(0.0042)	(0.0057)	(0.0036)
Employer sponsored insurance	0.4939	0.0875***	0.0922***	0.0824***
	(0.0008)	(0.0054)	(0.0067)	(0.0048)
Individually purchased insurance	0.0961	-0.0115***	-0.0125***	-0.0103***
	(0.0005)	(0.0022)	(0.0024)	(0.0023)
Public insurance	0.1241	-0.0110***	-0.0083***	-0.0137***
	(0.0006)	(0.0022)	(0.0024)	(0.0033)
Medicaid	0.1143	-0.0084***	-0.0030	-0.0140***
	(0.0005)	(0.0022)	(0.0022)	(0.0034)
Medicare	0.0087	-0.0001	-0.0004	0.0002
	(0.0002)	(0.0004)	(0.0006)	(0.0007)
Sample size		1,150,477	578,892	571,585

*Notes:*The data used was the ACS from 2008-2014. All outcomes are estimated under the specification in equation (4). Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

When analyzed by sex, the effects retain significance for both males and females with some change in magnitude by sex. Estimates for males are around a percentage point larger than those for females, with regards to the likelihood of having any insurance (6.54 percentage points compared to 5.1 percentage points), private insurance (7.5 percentage points compared to 6.6 percentage points) and ESI (9.2 percentage points compared to 8.2 percentage points). Additionally, the decline in the likelihood of individually purchasing insurance declines more for males than females. Females have a larger estimate for the decrease in likelihood of having public insurance than males: 1.4 percentage points compared to under 1 percentage point.

2.4.2 Labor Market Outcomes

Having shown that dependent mandates increase insurance coverage, I now turn to presenting results that examine the effects on labor market outcomes. I present separately the results from state dependent mandates and the results from the ACA dependent mandate.

2.4.2.1 State Dependent Mandates

I present the means and estimates on education and marital status from the CPS in Table 2.11, where I find evidence of an increase in educational attainment. Thirty percent of the sample are currently students, with 40 percent having less than a bachelor's degree at present and only about 9 percent having a bachelor's degree. I find no effect on the likelihood of being a college student, finishing high school, having some college but less than a bachelor's degree, or having a graduate degree. I do find evidence of an increase in education—about a 1 percentage point increase in the likelihood of having a bachelor's degree, a decrease of about 2 percentage points in the likelihood of having never attended any college courses and an increase of about 0.05 years of college attendance. For males, I find a slightly larger increase in the likelihood of obtaining a bachelors degree and a 4.4 percentage point decrease in the likelihood of not attending any college courses. About 19 percent of the sample is married, with just over 1 percent reporting being divorced. Overall and for females, I find no impact on the likelihood of being married or divorced, but I find a 0.6 percentage point decrease in the likelihood of being married for males.

Table 2.11: DDD Estimates of State Mandates on Education and Marital Status, Excluding States with Student Requirements

	Mean	DDD Estimates		
		All	Male	Female
College student	0.3015	0.0041	0.0099	0.0001
	(0.0004)	(0.0064)	(0.0063)	(0.0077)
High school degree, no college	0.3047	0.0101	0.0064	0.0136
	(0.0004)	(0.0087)	(0.0087)	(0.0098)
Some college, no bachelor's	0.4033	-0.0075	-0.0056	-0.0072
	(0.0004)	(0.0066)	(0.0093)	(0.0084)
Bachelor's degree	0.0876	0.0093**	0.0122**	0.0056
	(0.0002)	(0.0044)	(0.0058)	(0.0045)
Graduate degree	0.0073	-0.0001	0.0005	-0.0005
	(0.0001)	(0.0012)	(0.0016)	(0.0020)
Years of college†	1.7121	0.0574***	0.1002**	0.0028
	(0.0019)	(0.0183)	(0.0402)	(0.0172)
No college	0.1373	-0.0208***	-0.0440***	-0.0028
	(0.0006)	(0.0060)	(0.0085)	(0.0088)
Married	0.1885	-0.0032	-0.0056**	-0.0013
	(0.0003)	(0.0025)	(0.0024)	(0.0032)
Divorced	0.0114	0.0016	0.0009	0.0023
	(0.0001)	(0.0024)	(0.0020)	(0.0034)
Sample size		1,932,994	937,375	995,619

Notes: The data used was the CPS from 1986-2009. All outcomes are estimated under the specification in equation (3). Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

† Years of college is only asked of individuals who have attended college.

I present the means and estimates on labor market outcomes from the CPS in Table 2.12, where

I find no evidence of a decrease in labor supply, no evidence of an increase in unemployment and evidence of an increase in unemployment duration. About 76 percent of young adults are in the labor force, with just below 8 percent being unemployed. Overall, I find no increase the likelihood of being unemployed, in the labor force, being an unpaid family worker, working full time or being paid hourly. I do not find any effects on the changes in hours worked overall, hours worked at a respondent's main job or hours worked at other jobs. I do find almost a three week increase in unemployment duration and a 0.3 percentage point increase in the likelihood of being self-employed. By sex, I find about a 0.7 percentage point decrease in the likelihood of being unemployed for males, a 0.41 percentage point increase in the likelihood of being self-employed for females, a 1.6 percentage point decrease in the likelihood of being paid hourly for males and similarly sized increases in unemployment duration for both sexes.

Table 2.12: DDD Estimates of State Mandates, Excluding States with Student Requirements, on Labor Market Outcomes

		DDD Estimates		
	Mean	All	Male	Female
Unemployed	0.0772	-0.0027	-0.0068**	0.0001
	(0.0002)	(0.0022)	(0.0029)	(0.0030)
In labor force	0.7574	0.0031	-0.0107	0.0086
	(0.0003)	(0.0071)	(0.0086)	(0.0077)
Self-employed	0.0189	0.0033**	0.0018	0.0041**
	(0.0001)	(0.0016)	(0.0032)	(0.0017)
Unpaid family worker	0.0012	-0.0002	-0.0002	-0.0001
	(0.0000)	(0.0002)	(0.0003)	(0.0034)
Weekly hours†	35.8930	0.1621	0.0643	0.2231
	(0.0151)	(0.1025)	(0.1503)	(0.2186)
Weekly hours at non-main job(s)††	14.5552	-0.0984	0.0288	-0.1615
	(0.0476)	(0.5403)	(1.3202)	(0.8398)
Unemployment duration in weeks†††	13.9881	2.7872***	3.2497***	2.5432**
	(0.0726)	(0.7875)	(0.8930)	(1.0307)
Full time	0.4722	0.0075	-0.0023	0.0104
	(0.0004)	(0.0071)	(0.0073)	(0.0091)
Paid hourly	0.8214	-0.0083	-0.0164**	0.0001
	(0.0008)	(0.0053)	(0.0077)	(0.0060)
Sample size		1,932,994	937,375	995,619

Notes: The data used was the CPS from 1986-2009. All outcomes are estimated under the specification in equation (3). Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

† Asked of civilians who work.

†† Asked of civilians who reported working more than one job.

††† Asked of civilians who were looking for work or on layoff.

2.4.2.2 Affordable Care Act Dependent Mandate

In this section, I present the means and estimates from the ACS sample and CPS sample where I find a decline in hours worked (intensive margin), little evidence of a decline in likelihood of working (extensive margin) and an increase in the likelihood of living with one's parent(s). First, I present the results from the ACS sample in Table 2.13. Among the young adults targeted by the ACA about 35 percent live with their parents and 21 percent are married. I find about a 1.7 percentage point increase in the likelihood of living with at least one parent and no overall increase in the likelihood of being married. I do find an increase of 0.028 in the number of marriages but no change in the likelihood of being married or divorced in the last 12 months. Eighty percent are in the labor force, with about 9 percent being unemployed and 25 percent being a student. The usual weekly hours for these young adults are just over thirty. I find no effect on the likelihood of being a student, unemployed, or participating in the labor force. I do find about a decrease of 0.34 in weekly hours or about a twenty minute reduction.

Table 2.13: DD Estimates of the ACA Dependent Mandate, 23 to 29 Year Olds ACS Sample

		DD Estimates		
	Mean	All	Male	Female
Live with parent(s)	0.3472	0.0165***	0.0167***	0.0164***
	(0.0080)	(0.0040)	(0.0045)	(0.0042)
Married	0.2134	0.0153	0.0249**	0.0051
	(0.0007)	(0.0100)	(0.0095)	(0.0109)
Number of marriages	0.2589	0.0275***	0.0350***	0.0196
	(0.0008)	(0.0113)	(0.0105)	(0.0125)
Married in year	0.2097	0.0008	-0.0031	0.0038
	(0.0013)	(0.0032)	(0.0051)	(0.0035)
Divorced in year	0.0327	0.0017	0.0025	0.0011
	(0.0006)	(0.0013)	(0.0023)	(0.0020)
Self-employed	0.0289	0.0013	0.0023*	0.0002
	(0.0003)	(0.0010)	(0.0013)	(0.0010)
Student	0.2544	-0.0012	-0.0022	-0.0001
	(0.0007)	(0.0045)	(0.0048)	(0.0046)
Unemployed	0.0939	0.0005	0.0015	-0.0004
	(0.0005)	(0.0016)	(0.0017)	(0.0022)
In the labor force	0.8062	-0.0009	-0.0022	0.0001
	(0.0007)	(0.0019)	(0.0033)	(0.0027)
Usual weekly hours†	30.1650	-0.3387***	-0.2959*	-0.4087***
	(0.0299)	(0.0903)	(0.1503)	(0.0950)
Sample size		1150477	578,892	571,585

*Notes:*The data used was the ACS from 2008-2014. All outcomes are estimated under the specification in equation (4). Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

† This outcome is asked of civilians who work.

By sex, the results are similar to the overall sample. Both males and females are about 1.6 percentage points more likely to live with their parents. For males, there is an increase in number of marriages by 0.035 and a 2.5 percentage point increase in the likelihood of being married. Also for males, there is a 0.23 percentage point increase in the likelihood of being self-employed. The estimated effect on the change in usual weekly hours is larger for females than males: a decrease of 0.41 hours compared to a decrease of 0.30 hours. For both sexes, I find no effect on the likelihood of being a student, unemployed or being in the labor force.

Next, I present the results from the CPS sample in Table 2.14. The means are very close to those in the ACS sample. Overall, I find a 2.4 percentage point increase in the likelihood of living with at least one parent. I again find no effect on the likelihood of being unemployed or in the labor force. I find a decrease in weekly hours of about 0.33 hours, with no significant effect on the amount of hours worked at secondary jobs. I do not find an overall effect on the unemployment duration, the likelihood of being married or the likelihood of being self-employed.

Table 2.14: DD Estimates of the ACA Dependent Mandate, 23 to 29 Year Olds CPS Sample

		DD Estimates		
	Mean	All	Male	Female
Live with parent(s)	0.3408	0.0240***	0.0268***	0.0208***
	(0.0009)	(0.0039)	(0.0064)	(0.0055)
Married	0.2246	-0.0068	0.0076	-0.0218***
	(0.0008)	(0.0064)	(0.0074)	(0.0079)
Unemployed	0.0864	0.0014	-0.0027	0.0054**
	(0.0006)	(0.0021)	(0.0032)	(0.0022)
In the labor force	0.7888	-0.0068	-0.0041	-0.0092
	(0.0008)	(0.0041)	(0.0057)	(0.0072)
Self-employed	0.0256	0.0015	0.0014	0.0016
	(0.0003)	(0.0015)	(0.0022)	(0.0021)
Weekly hours†	37.8567	-0.3262**	-0.2861*	-0.3558*
	(0.0262)	(0.1332)	(0.1452)	(0.2005)
Weekly hours at non-main jobs††	14.8810	0.5450	0.7816	0.2965
	(0.0959)	(0.4306)	(0.6207)	(0.5659)
Unemployment duration in weeks†††	25.1624	-1.2936	-2.0381**	-0.1879
	(0.1979)	(0.8910)	(1.0012)	(1.3636)
Sample size		678,913	328,202	350,711

*Notes:*The data used was the CPS from 2008-2014. All outcomes are estimated under the specification in equation (4). Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

† This outcome is asked of civilians who work.

†† This outcome is asked of civilians who reported working more than one job.

††† This outcome is asked of civilians who were looking for work or on layoff.

By sex, the effects are similar to the overall effects. The estimated effect on the likelihood of living with at least one parent is larger for males than females (2.7 percentage points compared to 2.1 percentage points). For females, I find a 2.2 percentage point decrease in the likelihood of being married. Also for females, there is a 0.5 percentage point increase in the likelihood of being unemployed. Like in the ACS, the estimated effect on weekly hours is larger for females than males (a decrease of 0.36 hours compared to a decrease of 0.29 hours). For males, there is a significant decrease in the unemployment duration of about two weeks.

2.4.3 Additional Tests

In this section, I explore my results on insurance coverage and labor market outcomes. I present additional tests for the state dependent mandates and ACA dependent mandate separately.

2.4.3.1 State Dependent Mandates

I perform an analysis looking at outcomes of parents to better understand the effects of mandates. I use a DD estimation strategy using the variation in timing (first difference) and state (second difference). The DD estimating equation for outcome y_{iast} for a parent i age a living in state s at time t is:

$$y_{iast} = \alpha + \beta(Post_{st}) + \gamma x_i + \delta_s + \nu_t + \varepsilon_{iast} \tag{2.7}$$

The coefficient of interest is β. $Post_{st}$ is an indicator taking a value of one in state s if a dependent coverage policy is in place at time t. x_i contains individual controls for sex, education, age, age squared, an indicator for the presence of a spouse and race/ethnicity. δ_s and ν_t are fixed effects for state and time. I exclude states with a student eligibility requirement and restrict my analysis to parents who have at least one child in the age range of 19-24. I choose a maximum age of twenty four because it captures a lot of the age eligibility requirements without limiting the size of the sample. I conduct three analyses based on household composition. First, I look at all households. Second, I look at households where both parents are present. Third, I look at households where only one parent is present. In the households where both parents are present, I use the outcomes and demographics from the parent with the largest personal income.

Table 2.15 reports the effect of living in a state with a dependent mandate on insurance coverage of heads of households, where I find evidence of changing from a self-only ESI plan to a group plan. Overall, I find no effect on the likelihood of the head of household having any insurance coverage, private insurance coverage or ESI. There is a decrease of roughly 1 percentage point in the likelihood of a household purchasing insurance and about a 1.3 percentage point decrease in the likelihood of having public insurance. Among the heads of households who have ESI, there is a 2.32 percentage point increase in the likelihood of having a family plan instead of a plan that only covers themselves.

Table 2.15: DD Estimates of State Dependent Mandates on the Insurance of Heads of Household, CPS ASEC Sample

	All Households		Dual Parent Households		Single Parent Households	
	Mean	DD Estimates	Mean	DD Estimates	Mean	DD Estimates
Any insurance	0.8651	-0.0003	0.8878	-0.0011	0.7666	-0.0005
	(0.0013)	(0.0143)	(0.0012)	(0.0114)	(0.0038)	(0.0282)
Private insurance	0.8041	0.0121	0.8452	0.0135	0.6259	0.0041
	(0.0015)	(0.0135)	(0.0015)	(0.0106)	(0.0044)	(0.0286)
Employer sponsored	0.7555	0.0201	0.7992	0.0264**	0.5660	-0.0100
insurance	(0.0016)	(0.0145)	(0.0017)	(0.0123)	(0.0045)	(0.0277)
Individually purchased	0.0622	-0.0097**	0.0638	-0.0145***	0.0554	0.0116
insurance	(0.0009)	(0.0043)	(0.0011)	(0.0046)	(0.0021)	(0.0074)
Public insurance	0.0912	-0.0129**	0.0739	-0.0166***	0.1660	-0.0012
	(0.0011)	(0.0063)	(0.0011)	(0.0058)	(0.0033)	(0.0141)
Family plan, among	0.7378	0.0232**	0.7876	0.0126	0.5793	0.0633**
those with ESI†	(0.0025)	(0.0095)	(0.0027)	(0.0105)	(0.0058)	(0.0240)
Sample size	87768		71695		16073	

*Notes:*All outcomes are estimated under the specification in equation (5) using SHADAC enhance variables unless otherwise specified. Years used are 1996-2010. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

† This outcome is a non-SHADAC enhanced variable. Individuals who report having ESI are asked if they have a plan which covers only themselves or a group plan.

There are, however, several differences to note when analyzing dual parent and single parent households. The head of a dual parent household is 89 percent likely to have insurance coverage, which is 12 percent higher than the head of a single parent household. This disparity is present for private insurance coverage (a 22 percent gap) and for private insurance through ESI (a 23 percent gap). Among those with ESI, the head of a dual parent household is 79 percent likely to have a family plan which is 21 percent more likely than the head of a single parent household. When it comes to public insurance, the head of a single parent household is 17 percent more likely to have public insurance, which is more than double the likelihood of that of the head of a single parent household.

Looking at the point estimates by household composition, the effects are different. The head of a dual parent household is 2.6 percentage points more likely to have ESI, 1.5 percentage points less likely to have individually purchased insurance and 1.7 percentage points less likely to have public insurance. For heads of dual parent households, there is no effect on the likelihood of having any insurance, private insurance or a family plan among those with ESI. For heads of a single parent household the only significant effect is a 6.3 percentage point increase in the likelihood of having a family plan among those with ESI. For heads of single parent households, there is no effect on the likelihood of having any insurance, private insurance, ESI, individually purchased insurance or public insurance.

Table 2.16 reports the effect of living in a state with a dependent mandate on labor market outcomes of heads of households, where I find no evidence of a change in labor force participation or the likelihood of being unemployed. Overall, I find no effect on the likelihood of changing occupation, the number of employers, or firm size. For heads of dual parent households, I find a decrease of 0.01 in the number of employers during the last year and an increase in firm size of 31 employees. For heads of single parent households, I find an 2.1 percentage point increase in the likelihood of changing occupation in the last year and a 0.036 increase in the number of employers in the last year.

Table 2.16: DD Estimates of State Dependent Mandates on Labor Market Outcomes of Heads of Households, CPS ASEC Sample

	All Households		Dual Parent Households		Single Parent Households	
	Mean	DD Estimates	Mean	DD Estimates	Mean	DD Estimates
In the labor force	0.7991	0.0038	0.7984	0.0075	0.8018	-0.0094
	(0.0014)	(0.0082)	(0.0016)	(0.0077)	(0.0034)	(0.0132)
Unemployed	0.0287	-0.0035	0.0248	-0.0036	0.0454	-0.0034
	(0.0006)	(0.0032)	(0.0006)	(0.0034)	(0.0018)	(0.0087)
Changed occupation	0.1145	-0.0022	0.1094	-0.0080	0.1365	0.0213**
	(0.0012)	(0.0050)	(0.0013)	(0.0065)	(0.0030)	(0.0100)
Number of employers†	1.1008	-0.0014	1.0959	-0.0101*	1.1227	0.0362**
	(0.0014)	(0.0044)	(0.0015)	(0.0059)	(0.0036)	(0.0133)
Firm size	588.4128	20.0795	580.1492	30.9161*	624.6937	-27.8168
	(2.2445)	(15.2097)	(2.4699)	(15.2799)	(5.3537)	(21.7082)
Sample size	98004		80022		17982	

Notes: All outcomes are estimated under the specification in equation (5). Years used are 1996-2010. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

† This outcome is a measure of job changes among those who were employed in the last year rather than a count of total employers.

Next, I examine the effect of state dependent mandates on ESI policyholders' income and plan characteristics. I use a DDD estimation strategy using the variation in timing (first difference), state (second difference) and firm size (third difference). Firm size is used as the third difference since larger firms are more likely to self-insure and thus not be bound by state mandates. The DDD estimating equation for outcome y_{iast} for an individual i living in state s at time t is:

$$y_{ist} = \beta(Post_{st} \times SmallFirm_i) + \gamma_{it} + \eta_{is} + \nu_{st} + \theta_t + \psi_s + SmallFirm_i + \pi x_i + \varepsilon_{ist} \tag{2.8}$$

The coefficient of interest is β. $Post_{st}$ is an indicator taking a value of one in state s if a dependent coverage policy is in place at time t. x_i contains individual controls for sex, education, age, age squared, race/ethnicity, marital status, occupation and industry. $SmallFirm_i$ is an indicator taking a value of one if an individual i works at a firm with less than 100 employees. ψs and θ_t are fixed effects for state and time. γ_{it}, η_{is} and ν_{st} are the first order interactions of the firm size indicator, state and time, respectively.

First, I look at the outcomes of ESI family plan policyholders. I estimate the effect on income from wages (in 1999 dollars) for evidence of a decrease in wages to offset the increased cost imposed on firms by state dependent mandates. Table 2.17 reports the results. The mean income for ESI family plan policyholders is $42,731.11. I find an negative and insignificant decrease in income from wages of $289.28. I do not log transform the income from wages, since there is not a significant mass of individuals with zero income by virtue of the sample being restricted to ESI family plan policyholders.

Table 2.17: DDD Estimates on ESI Family Plan Policyholders' Wages

Outcome	Mean	DDD Estimate
Income from wages†	42731.11	-289.2798
	(177.2651)	(1909.2607)
Sample size		83,462

Notes: The data used was the CPS ASEC 1996-2010. Values are in 1999 dollars. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.
† There is no significance when using the natural logarithm transformation of income from wages

Next, again among ESI family plan policyholders, I look for evidence of changes in plan characteristics. In Table 2.18, I report the results for the likelihood of an employer paying no premiums and the employer contribution (in 1999 dollars). Most employers paid part of or all of premiums, with only 5.9 percent not paying any premiums. I find roughly a 1 percentage point increase in the likelihood of an employer paying no premiums. The average employer contribution to insurance was $3,982.14. I find a negative and insignificant decrease of $69.21 in employer contribution.

Table 2.18: DDD Estimates on ESI Family Plan Policyholders' Benefits

Outcome	Mean	DDD Estimate
Employer paid no premiums	0.0590	0.0099**
	(0.0004)	(0.0045)
Employer contribution†	3982.137	-69.2119
	(3.9866)	(45.7878)
Sample size		414,161

Notes: The data used was the CPS ASEC 1996-2010. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

† Values are in 1999 dollars.

In Table 2.19, I expand my sample to include all ESI policyholders who have at least one potential dependent.[6] I look at the likelihood of an ESI policyholder having a family plan instead of a plan which only covers the policyholder. Just over half of the sample report having a family plan. I find an insignificant decrease of 0.01 percentage points in the likelihood of having a family plan.

[6] I specifically include individuals who have any children in the household or who report being married.

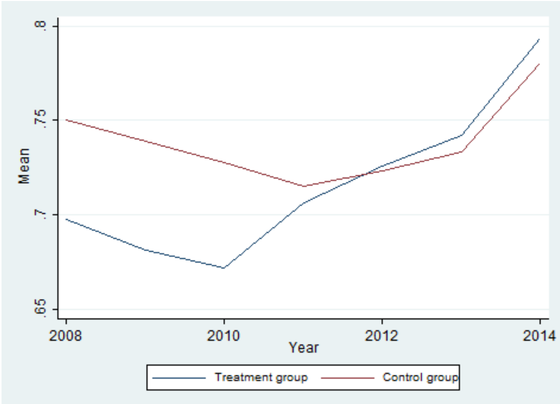
Table 2.19: DDD Estimates on Type of ESI for Policyholders

Outcome	Mean	DDD Estimate
Family plan	0.5334	-0.0001
	(0.0007)	(0.0067)
Sample size		534,860

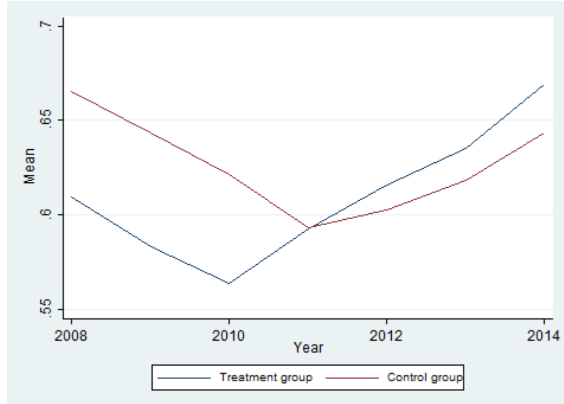
Notes: The data used was the CPS ASEC 1996-2010. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

2.4.3.2 Affordable Care Act Dependent Mandate

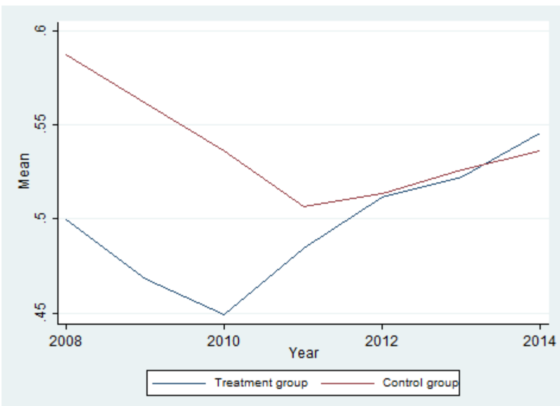
I further explore the significant results by plotting the means of the control and treatment groups. In order for the results to be valid the parallel trends assumption needs to hold. I plot the trends of each outcome looking for evidence that the parallel trends assumption is violated. Figure 2.2 presents the graphs of yearly means for insurance outcomes using the ACS data. The parallel trends assumption looks to be satisfied. From 2008-2010, the plotted means follow similar paths.



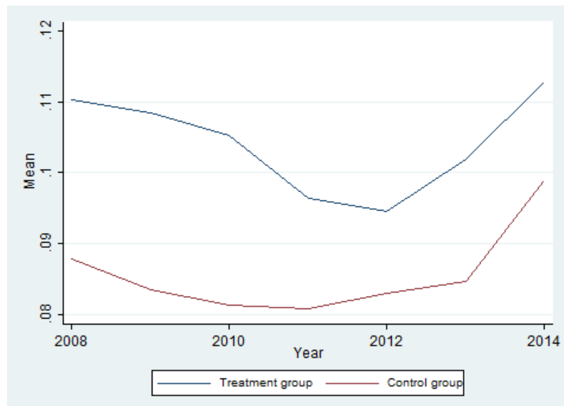
(a) Any Insurance



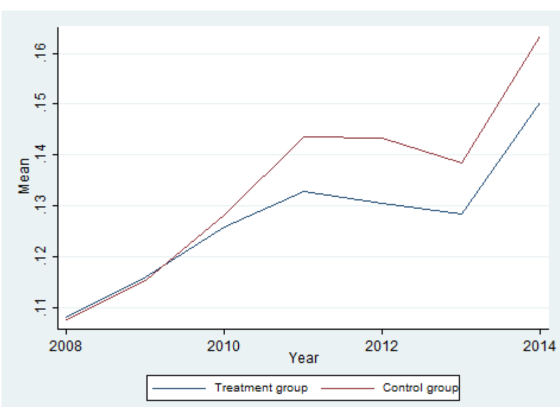
(b) Private Insurance



(c) ESI



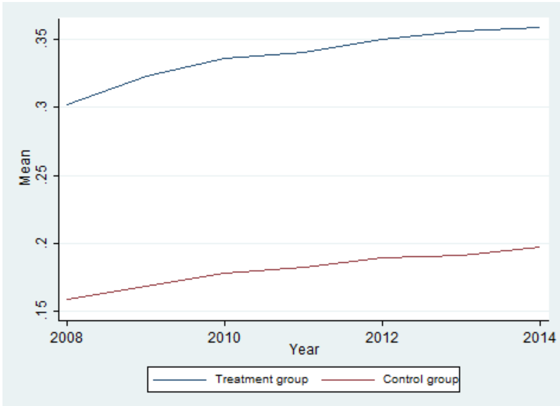
(d) Individually Purchased Insurance



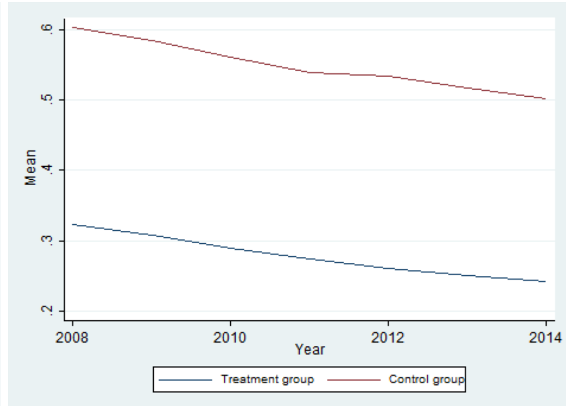
(e) Public Insurance

(f) Medicaid

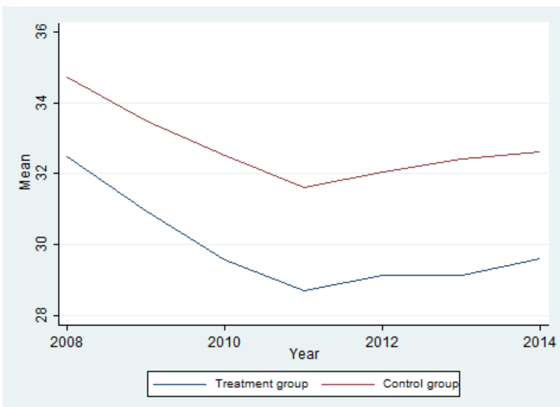
Figure 2.2: Insurance Outcomes from ACS Data



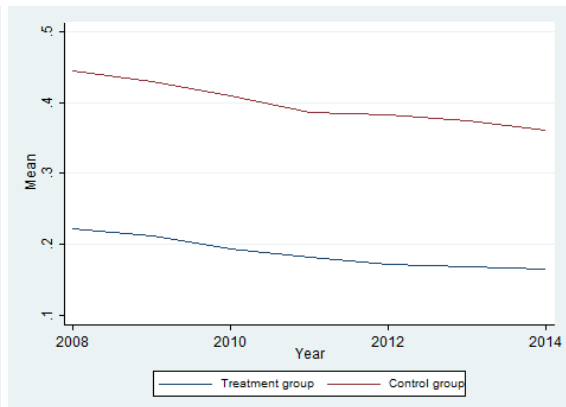
(a) Live with Parent(s)



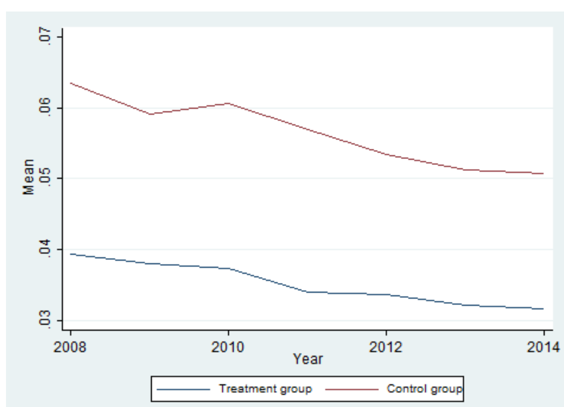
(b) Number of Marriages



(c) Usual Weekly Hours



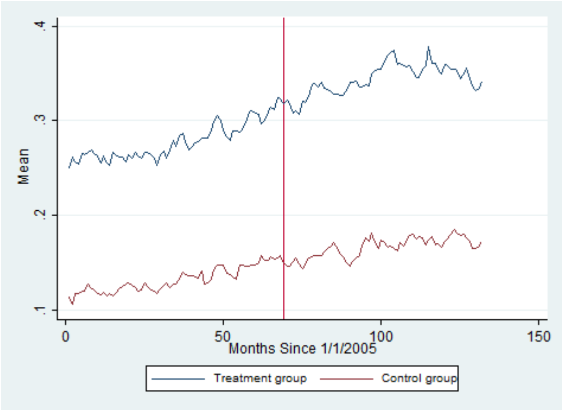
(d) Marriage Among Males



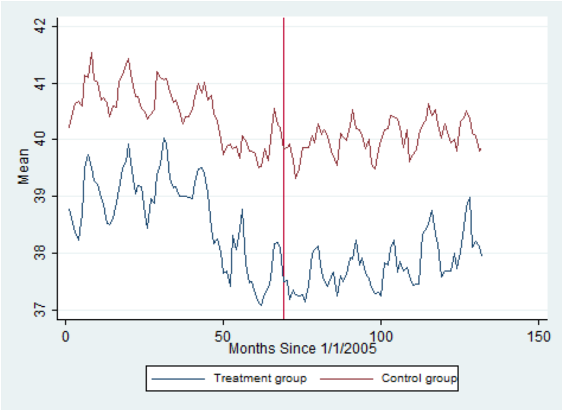
(e) Self-employment Among Males

Figure 2.3: Non-insurance Outcomes from ACS Data

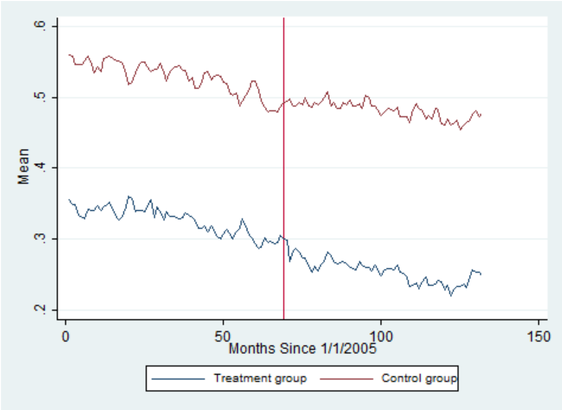
Figure 2.3 presents the graphs of yearly means for ACS labor market outcomes with significance. Again, for the majority of outcomes the parallel trends assumption is satisfied.



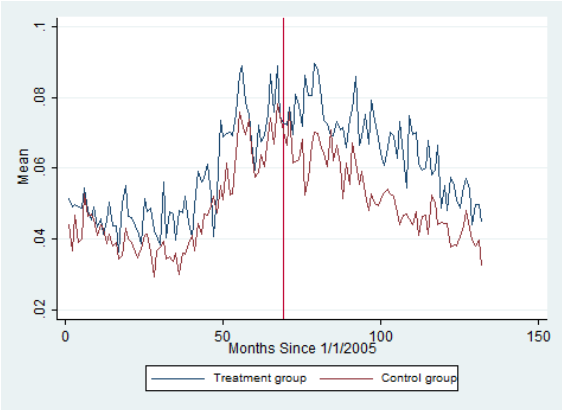
(a) Live with Parent(s)



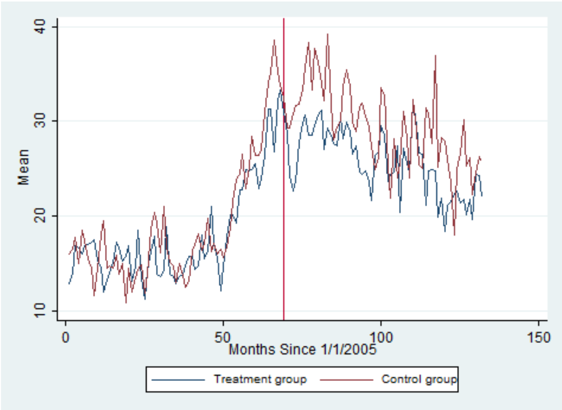
(b) Usual Weekly Hours



(c) Marriage Among Females



(d) Unemployment Among Females



(e) Unemployment Duration Among Males

Figure 2.4: Non-insurance Outcomes from CPS Data

Figure 2.4 presents the graphs of monthly means for CPS labor market outcomes with significance. For each outcome, it appears that parallel trends is satisfied.

2.5 Conclusions

My findings show that dependent mandates were effective in increasing insurance coverage among young adults and had an impact on non-insurance outcomes. Looking at state dependent mandates, I find a 6 percent gain in any insurance coverage. The gain is mostly comprised of an 11 percent gain in ESI, which contributes to an overall 7.5 percent gain in private coverage. When the analysis excludes states with student requirements, I find a 3.3 percent gain in any insurance coverage, a 4.8 percent gain in private insurance and a 9.9 percent gain in ESI. Turning to the ACA dependent mandate, I find an 8.2 percent gain in any insurance coverage, a 11.8 percent gain in private insurance coverage, a 17.7 percent gain in ESI coverage, a 12 percent decrease in individually purchased coverage and a 8.9 percent decrease in public insurance coverage. Under the ACA dependent mandate, there is some evidence of crowding in, as there is a reduction in public insurance among the targeted population. There is also a shift in the type of private plans young adults have with there being a reduction in individually purchased plans as young adults switch to ESI.

Several effects of note become apparent from looking at the results from state and federal dependent mandates. Looking for heterogeneity in estimates by sex, I find that the magnitudes of the estimated effect of dependent mandates on insurance is larger for males than females. The exception to this is that the decline in public insurance is larger for females than males under the ACA dependent mandate. The difference in magnitudes of the results appear to be in line with what is expected since the ACA is binding on self-insured firms. The estimated effects of state dependent mandates with marital and age eligibility criteria are smaller than the estimated effects of the ACA dependent mandate. The point estimates of the state dependent mandates are 40 percent, 41 percent and 55 percent of the point estimates for the ACA dependent mandates effect on any insurance, private insurance and ESI, respectively. As noted earlier, about 55 percent of workers with health insurance coverage were covered by a self-insured firm, so this would lead to an expectation that the state dependent mandates should be around 45 percent of the size of a federally binding mandate, which is consistent with the magnitudes I find.

Despite the efficacy of mandates in increasing insurance coverage, I find no effect on self-rated health of young adults. Barbaresco et al. (2015) find that the ACA dependent mandate resulting in a 1.4 percentage point increase in the likelihood of reporting excellent health. I do not find a similar effect for state dependent mandates. I find an insignificant 0.6 percentage point decrease in the likelihood of reporting excellent health. However, I am unable to reasonably rule out an effect of the order found in Barbaresco et al. (2015) because my estimates are less precise and include up to a 1.8 percentage point increase in the 95 percent confidence interval.

To further understand the effect of dependent mandates on insurance, I looked at the effects on heads of households who have children aged 19-24. I find no evidence that dependent mandates result in increased insurance coverage among parents. In fact, I can reasonably rule out effects larger than 3.3 percent for the heads of households. I do find some evidence that the type of plan the heads of households have changes in response to a dependent mandate. I find a 15.6 percent decrease in the likelihood of having individually purchased insurance, a 14 percent decrease in the likelihood of having public insurance coverage and a 3.1 percent increase in the likelihood of having a family plan among those with ESI. I further examine the effects on parents by looking at households with one parent present compared to households with two parents present. The percent of single parent households with ESI is over 23 percent less than dual parent households, but the estimated effect of switching to a family plan is much larger for single parent households. Taken together, this can be informative for further policies targeting uninsurance among young adults—any policies aimed at increasing ESI among single parents would likely complement dependent mandates and help reduce uninsurance among dependents in single parent households.

Even with no changes in the likelihood of having any insurance coverage among the heads of households, it may be reasonable to expect some labor changes in response to a dependent mandate. If a parent has ESI, a dependent mandate may increase job lock since now their adult child's insurance is tied to their employment. Alternatively, parents who do not have ESI may seek out jobs which offer ESI now that they have the added benefit of covering older dependents. I can reasonably rule out effects of 2.9 and 4.5 percent for labor force participation among dual parent and single parent households, respectively. However, in my analysis I define the head of a dual household as the one with the highest personal income, so by construction they are more likely to be in the labor force making the dual parent household estimates unreliable.

Despite the evidence showing the lack of an effect on labor force participation, there is differing evidence of job lock by household composition. The heads of dual parent households have about a 1 percent decrease in the number of job changes during the last year, while the heads of single parent households have a 3.2 percent increase in job changes during the last year in addition to a 15.6 percent increase in the likelihood of changing their type of occupation. The decrease in job mobility for heads of dual parent households is consistent with an increase in job lock following a dependent mandate. The increase in job mobility for heads of single parent households, however, is not consistent with increased job lock. Furthermore, coupled with the lack of increase in likelihood of having ESI among the heads of single parent households it does not appear they are seeking out jobs that offer ESI. Yet, not all ESI plans are equal. Some firms may only offer individual plans, require the employer to pay the full premiums for dependents or be exempt under ERISA from following state dependent mandates. It is possible that heads of single parent households who already have ESI spend time seeking out employers whose ESI plans are better suited for their needs.

I examine the effect of dependent mandates on ESI policyholders' income and plan characteristics. I find no evidence that employers shift the cost of dependent mandates to ESI family plan policyholders in the form of decreased wages. I do find evidence that employers are offsetting the increased cost imposed by the mandates by no longer paying for premiums. I find a 17 percent increase in the number of employers that pay no part of the employee's premiums. I do not find an effect on the dollar value of an employer's contribution for health insurance. To be sure that the sample of ESI family plan policyholders is not changing in response to an effect of the mandates, I estimate the likelihood of holding a family plan among all ESI policyholders. I can reasonably rule out effects that are larger than 2.5 percent of the mean.

I find evidence that dependent mandates affect young adults' labor market outcomes. I find that both the state and ACA dependent mandates increase self-employment among young adults. Under the state dependent mandates I find a 17.5 percent increase in the likelihood of being self-employed and, under the ACA dependent mandate, I find a 8 percent increase in the likelihood of being self-employed for males in the ACS sample. I find no evidence of state dependent mandates resulting in a change in total weekly hours or weekly hours at jobs other than a main job. Under the ACA dependent mandate I find young adults in both the CPS and ACS sample worked roughly 20 minutes less a week, with the decrease being larger for females than males. Dependent mandates did not deter young adults' participation in the labor force—overall, for each sample, I can reasonably rule out changes larger than 2.3 percent of the mean. Looking at unemployment duration, I find that the state dependent mandates resulted in an increase of 20 percent or about 3 weeks, which is consistent for the overall sample and by sex. Looking at the ACA dependent mandate, I find a decrease in unemployment duration of 8 percent or about 2 weeks for males. It is worth noting that the mean unemployment duration is nearly double for the period used in the ACA dependent mandate analysis than that of the period used in the state dependent mandate analysis.

Under my analysis of state dependent mandates, I additionally find an increase in educational attainment among targeted individuals. I find a 10.6 percent increase in the likelihood of having a bachelor's degree, a 15 percent decrease in the likelihood of having never taken a college course and a 3.4 percent increase in years of college attended among individuals who have attended college at some point. These results are consistent with Dillender (2014), who looks at individuals in their late twenties and early thirties who were previously eligible under a state dependent mandate. He finds an increase in completing college education, an increase of having some college education and an increase in years of college education.

Looking at marital and living outcomes for young adults, I find some evidence of dependent mandates affecting their decisions. With regards to household composition, I find that the ACA dependent mandate resulting in about a 5 to 7 percent increase in the likelihood of living with at least one parent. Looking at marital status, I find no evidence of the ACA dependent mandate resulting in changes in the likelihood of being married or divorced in the last year. I do find that the ACA dependent mandate resulted in a 10.6 percent increase in the number of marriages dependents have had in their lifetime. Looking at ACA dependent mandate's effect on the likelihood of being married, I find no overall effect in either the CPS or ACS sample. For males in the ACS, I find an 11.6 percent increase in the likelihood of being presently married but no significant effect in the CPS. For females in the CPS, I find a 9.7 percent decrease in the likelihood of being presently married but no effect in the ACS. Under state dependent mandates, I find no effect on the likelihood of being married or divorced but I do find about a 3 percent decrease in the likelihood of being presently married among males.

In conclusion, I have shown that dependent mandates lead to an increase in insurance coverage among the targeted population and, furthermore, result in changes on some labor market outcomes. I have contributed to the existing literature on state dependent mandates by using an original data set on mandates and by extending the period of analysis. I also contribute to the existing literature on the ACA dependent mandate by estimating results while controlling for previously eligible young adults and omitting states that have dependent mandates which extend into the traditional control group ages of 27 to 29. I have shown evidence that dependent mandates encourage entrepreneurship among young adults and do not discourage labor supply among targeted young adults or their parents.

Chapter 3

The Effects of Health Insurance on Inpatient Medical Care: Evidence from State Dependent Mandates

3.1 Introduction

Health economists have done considerable research on the effects of dependent mandates on insurance, health and non-health outcomes exploiting both federal and state mandates. The Affordable Care Act (ACA) dependent mandate has been widely studied resulting in a well-documented gain of insurance coverage among eligible young adults. However, few studies have focused on the utilization of inpatient care following the ACA mandate. Antwi et al. (2015) find that the ACA dependent mandate led to an increased use of inpatient care among eligible young adults. Akosa Antwi et al. (2016) find that the ACA dependent mandate increased private coverage and decreased Medicaid coverage of childbirth among targeted women. More broadly looking at the use of inpatient care among young adults, Anderson et al. (2012) find that when young adults age out of their parents' insurance plans they use less inpatient care. Antwi et al. (2015) find no effects on the intensity of care provided when they look at the length of stay, number of procedures or total charges. No studies have leveraged the rich variation in state dependent mandates to study the effect of young adult insurance mandates on inpatient care.

When looking at the use of inpatient care among young adults it is of particular interest to look at mental health care. Mental health is an important issue for the well-being of young adults. Suicide is the leading cause of death for individuals aged fifteen to twenty-nine, mental illness has considerable comorbidities and mental health issues are the leading cause of disability (World Health Organization). Stigma is a potential barrier to receiving mental health care. Most U.S. adults believe that treatments for mental health issues are effective but considerably fewer believe that individuals are sympathetic toward individuals suffering from a mental health condition

(Manderscheid et al., 2010). Additionally the media is more likely to portray negative mental health stories than positive stories (Wahl, 2003) and health professionals as well as the public are more likely to expect discrimination and poor outcomes following treatment for individuals with mental illness (Jorm et al., 1999). If stigma prevents the use of primary care to address mental health problems then hospital care may be the first line of care for many individuals. Providing additional evidence of how insurance gains affect the mental health of young adults is important as United States policymakers continue to pursue healthcare reforms.

In this literature the question of how insurance impacts the mental health of young adults has not been paid a proportionate amount of attention given substantial risk of mental health issues for young adults. Following the ACA dependent mandate young adults are more likely to have inpatient discharges for mental illness and more likely to increase spending on mental health and substance abuse (Antwi et al., 2015; Fronstin, 2013; Saloner and Lê Cook, 2014; Golberstein et al., 2015). However, Saloner et al. (2017) find a decrease in specialty substance abuse treatment following the ACA dependent mandate.

I use the Nationwide Inpatient Sample (NIS) and a compilation of original legal data on state dependent mandates to provide new evidence on the utilization of inpatient care following a dependent mandate. I exploit variation in state, timing and eligibility in a differences-in-differences-in-differences (DDD) framework. Specifically, I explore the effects on form of payment, intensity of care, total charges, disposition at discharge and the likelihood of a discharge for mental health issues. I then repeat my analysis on the sample of mental health inpatient discharges.

I find dependent mandates led to an increased likelihood of young adults primary source of payment being some form of insurance, with the overall gain largely due to an increase in private insurance and a decrease in self-pay. Consistent with the hypothesis that insurance lowers the cost of care and thus increases consumption, following dependent mandates I find increased care provided for young adults in the form of longer stays and more procedures performed. Consistent with the increased care received, I find increases in the total charges for each discharge. I find an increased likelihood of inpatient discharges being for mental health.

3.2 Data

The data used in my analysis is the Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality. Each year the NIS contains roughly a twenty percent sample of United States hospitals excluding long-term hospitals, psychiatric hospitals, and alcoholism and chemical dependency facilities. States must agree to be included in the NIS which results in states entering, and occasionally exiting, the sample during different years.

Table 3.1: States Included in my Sample

State	First Year	Last Year	Missing Years	Earliest Mandate	Age Cutoff
AR	2004	2010			
AZ	1989	2010	2002		
CO	1988	2010		2006	24
IL	1988	2010		2009	25
IN	2003	2010		2007	23
KS	1993	2010			
MD	1993	2010		2008	24
ME	1999	2010	2003-2006	2007	24
MI	2001	2010			
MO	1995	2010		2008	25
MN	2001	2010		1994	24
NC	2000	2010			
NH	2003	2010			
NV	2002	2010			
OR	1993	2010		1998	22
TN	1995	2010		1986	23
UT	1997	2010		1993	25
VT	2001	2010			
WA	1988	2010		2009	24
WI	1989	2010			

Notes: The year reported for the earliest mandate are the first year a month had a mandate in effect. It is not reporting the first fully treated year. The age cutoff is the oldest age an individual may be and still retain eligibility under the mandate.

I omit states that have mandates with a student eligibility criterion as well as the states of

Hawaii and Massachusetts which have undergone sweeping health insurance reforms. In Table 3.1 I list the states that are included in my sample, the years each state participated in the NIS, the effective year of the state's earliest dependent mandate and the age cutoff for eligibility under the mandate. My final sample is composed of twenty states. Eleven of these states have mandates with nine implementing mandates during my period of analysis. I use NIS data from 1988 to 2010. I exclude the fourth quarter of 2010 due to the ACA dependent mandate going into effect in September 2010. The unit of observation for my analysis represents an inpatient discharge. Each observation contains information about the patient's demographics, clinical outcomes, admission, disposition and source of payment. I restrict my analysis to individuals aged 19 to 29.

3.3 Empirical Strategy

My estimation strategy takes advantage of quasi-experimental variation in the adoption of mandates by states. I employ a differences-in-differences-in-differences (DDD) estimation strategy using the variation in timing (first difference), state (second difference) and age eligibility (third difference). The DDD estimating equation for hospital h in state s with eligibility e at time t is:

$$y_{hset} = \beta_0 + \beta_1 (Post_{st} \times Eligible_{es}) + \gamma_t + \delta_s + \beta_2 Eligible_{es} + \zeta_{st} + \eta_{et} + \theta_{se} + \lambda_m + \phi_h + \varepsilon_{hset} \quad (3.1)$$

The coefficient of interest is β_1. $Eligible_{es}$ is an indicator taking the value of one if a patient is in the eligible age group under a dependent mandate in state s. For states that have not adopted a mandate $Eligible_{es}$ takes a value of one if the patient is 24 years of age or younger. $Post_{st}$ is an indicator taking the value of one if state s has a mandate in place at time t. γ_t is a time fixed effect, δ_s is a state fixed effect, ζ_{st} is a state-time fixed effect, η_{et} is an eligibility-time fixed effect, θ_{se} is a state-eligibility fixed effect, λ_m is a month fixed effect and ϕ_{hs} is a hospital-state fixed effect. ε_{hset} is the effect of variables omitted from the equation. I estimate additional specifications which include controls for patient age, patient race, an indicator for weekend admission, the number of diagnosis and major diagnostic category (MDC).

I begin by splitting the sample of 19-29 year olds into two groups. The first group consists of non-neonatal and non-maternal inpatient discharges. The second group consists of non-neonatal and non-maternal mental health inpatient discharges. Within each group I look at the same set of outcomes. First, I look at the individuals primary form of payment. I estimate the likelihood of the primary form of payment being through insurance, private insurance, Medicaid, Medicare and self-pay. In the NIS it is not specified if the patient is the policyholder or a dependent on the insurance policy. Second, I proceed to look for changes in the characteristics of the discharge; I examine the outcomes for length of stay, the log of length of stay and the number of procedures performed. Third, I look for changes in the patient's disposition during discharge: routine, a hospital transfer, home health care or against medical advice. Fourth, I look for changes in the total charges and the log of total charges. Last, I look at the likelihood of being admitted for mental health, alcohol or drug use disorders, and drug related poisonings or injuries.[1]

3.4 Results

3.4.1 Non-neonatal and Non-maternal Inpatient Visits

In Table 3.2, I present the estimated DDD coefficients and means for the estimates on primary payment source. For the full sample I find eligible young adults are over 2 percentage points more likely to pay with some form of insurance. The net gain in insurance coverage comes largely from a 3 percentage point increase in private insurance and a 2.7 percentage point decrease in self-pay. There is considerable heterogeneity among results by sex. I find no increase in the likelihood of paying with some form of insurance for females. There is a 3 percentage point increase in the likelihood of paying with private insurance that is offset by a 1.1 decrease in the likelihood of paying with Medicare and a 1.5 percentage point decrease in the likelihood of self-pay. For males, I find a 3.7 percentage point increase in the likelihood of paying with insurance. The overall gain

[1] I define mental health as the diagnosis-related groups (DRGs) that are under the major diagnostic category (MDC) "Mental Diseases and Disorders." For alcohol or drug used disorders I use the DRGs under the MDC "Alcohol/Drug Use or Induced Mental Disorders." For drug related poisonings or injuries I use the DRGS under the MDC "Injuries, Poison and Toxic Effect of Drugs."

is due to a 3 percentage point increase in the likelihood of paying with private insurance and a 3.8 percentage point decrease in self pay.

Table 3.2: Primary Payment Source

	Panel A. full sample				
	Any insurance	Private insurance	Medicaid	Medicare	Self-pay
Baseline model	0.0241***	0.0399***	-0.0059*	-0.0098**	-0.0281***
	(0.0039)	(0.0044)	(0.0028)	(0.0036)	(0.0039)
+Risk controls	0.0229***	0.0312***	-0.0016	-0.0066	-0.0270***
	(0.0030)	(0.0041)	(0.0048)	(0.0035)	(0.0033)
Mean	0.7344	0.4391	0.2455	0.0498	0.1934
Sample size	1,312,447	1,312,447	1,312,447	1,312,447	1,312,447
	Panel B. female sample				
	Any insurance	Private insurance	Medicaid	Medicare	Self-pay
Baseline model	0.0058	0.0390***	-0.0168**	-0.0163**	-0.0131**
	(0.0057)	(0.0035)	(0.0059)	(0.0052)	(0.0040)
+Risk controls	0.0081	0.0296***	-0.0104	-0.0111*	-0.0146***
	(0.0051)	(0.0054)	(0.0057)	(0.0052)	(0.0035)
Mean	0.8035	0.4712	0.2878	0.0445	0.1387
Sample size	662,423	662,423	662,423	662,423	662,423
	Panel C. male sample				
	Any insurance	Private insurance	Medicaid	Medicare	Self-pay
Baseline model	0.0441***	0.0400**	0.0074	-0.0033	-0.0438***
	(0.0076)	(0.0109)	(0.0055)	(0.0062)	(0.0065)
+Risk controls	0.0367***	0.0318**	0.0072	-0.0023	-0.0380***
	(0.0067)	(0.0091)	(0.0078)	(0.0060)	(0.0059)
Mean	0.6640	0.4063	0.2024	0.0553	0.2492
Sample size	650,024	650,024	650,024	650,024	650,024

Notes: Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

In Table 3.3, I present the estimated effects on the characteristics of inpatient discharges. For the full sample I find that the length of stay increases by 0.28 days. The number of procedures increases by 0.04 and the time elapsed until the first procedure increases by 0.07 days. The results by sex are similar to those of the full sample.

Table 3.3: Characteristics of Inpatient Discharges

	Panel A. full sample			
	Length of stay	Log length of stay	Number of Procedures	Days until first procedure
Baseline model	0.1673**	0.0328**	-0.0283*	0.0295
	(0.0613)	(0.0101)	(0.0122)	(0.0307)
+Risk controls	0.2772***	0.0476***	0.0383**	0.0745**
	(0.0384)	(0.0066)	(0.0313)	(0.0219)
Mean	4.4116	1.1051	1.0963	0.8848
Sample Size	1,313,108	1,255,439	1,313,879	368,464
	Panel B. female sample			
	Length of stay	Log length of stay	Number of Procedures	Days until first procedure
Baseline model	0.1307*	0.0330**	-0.0214	0.0063
	(0.0590)	(0.0107)	(0.0147)	(0.0182)
+Risk controls	0.2359***	0.0511***	0.0329**	0.0631**
	(0.0428)	(0.0096)	(0.0134)	(0.0208)
Mean	4.0920	1.0640	1.0267	0.8855
Sample Size	662,797	638,245	663,121	183,068
	Panel B. male sample			
	Length of stay	Log length of stay	Number of Procedures	Days until first procedure
Baseline model	0.1926**	0.0310**	-0.0391*	0.0568
	(0.0653)	(0.0094)	(0.0169)	(0.0504)
+Risk controls	0.3072***	0.0427***	0.0383*	0.0861**
	(0.0421)	(0.0057)	(0.0165)	(0.0333)
Mean	4.7373	1.1475	1.1671	0.8842
Sample Size	650,311	617,194	650,758	185,396

Notes: Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

In Table 3.4, I present the estimated effects on the patients' disposition at discharge. For the full sample I find a decrease of 0.42 percentage points in the likelihood of a routine discharge. I find a 0.32 percentage point increase in the likelihood of transferring to another hospital. For females I find a 0.95 percentage point decrease in the likelihood of a routine discharge and a 0.42 percentage point increase in the likelihood of transferring to another hospital. For males I find a 0.21 percentage point increase in the likelihood of transferring to another hospital and a 0.032 percentage point decrease in the likelihood of leaving against medical advice.

Table 3.4: Patient's Disposition at Discharge

	Panel A. full sample			
	Routine	Hospital transfer	Home health care	Against medical advice
Baseline model	0.0015	0.0025**	-0.0027**	-0.0010
	(0.0031)	(0.0009)	(0.0008)	(0.0014)
+Risk controls	-0.0042*	0.0032***	-0.0005	-0.0018
	(0.0019)	(0.0007)	(0.0004)	(0.0011)
Mean	0.8843	0.0156	0.0203	0.0292
Sample Size	1,313,879	1,313,879	1,313,879	1,313,879
	Panel B. female sample			
	Routine	Hospital transfer	Home health care	Against medical advice
Baseline model	-0.0044	0.0035**	-0.0018	0.0001
	(0.0049)	(0.0014)	(0.0011)	(0.0012)
+Risk controls	-0.0095*	0.0042**	0.0003	-0.0004
	(0.0041)	(0.0013)	(0.0010)	(0.0009)
Mean	0.9056	0.0145	0.0184	0.0238
Sample Size	663,121	663,121	663,121	663,121
	Panel B. male sample			
	Routine	Hospital transfer	Home health care	Against medical advice
Baseline model	0.0080***	0.0014	-0.0037**	-0.0022
	(0.0017)	(0.0009)	(0.0012)	(0.0018)
+Risk controls	0.0020	0.0021*	-0.0015	-0.0032*
	(0.0012)	(0.0009)	(0.0010)	(0.0016)
Mean	0.8626	0.0168	0.0221	0.0346
Sample Size	650,758	650,758	650,758	650,758

Notes: Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

In Table 3.5, I present the estimated effects on the total charges incurred. Overall I find an increase of $322.21 and an increase of 0.04 in the log of total charges. For females I find only a significant increase of 0.04 in the log of total charges. For males I find an increase of $553.02 in total charges and a 0.04 increase in the log of total charges.

Table 3.5: Charges

	Panel A. full sample	
	Total charges	Log total charges
Baseline model	-183.8742	0.0078
	(124.5600)	(0.0066)
+Risk controls	322.2111**	0.0421***
	(122.7313)	(0.0060)
Mean	8019.989	8.4214
Sample Size	1,308,040	1,308,040
	Panel B. female sample	
	Total charges	Log total charges
Baseline model	-383.5192	0.0085
	(207.7072)	(0.0068)
+Risk controls	12.8634	0.0416***
	(110.1229)	(0.0072)
Mean	7289.768	8.3903
Sample Size	660,091	660,091
	Panel B. male sample	
	Total charges	Log total charges
Baseline model	-49.1268	0.0062
	(190.391)	(0.0082)
+Risk controls	553.0219*	0.0407***
	(226.5165)	(0.0064)
Mean	8763.895	8.4530
Sample Size	647,949	647,949

Notes: Values are reported in 1988 USD. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

In Table 3.6, I present the likelihood of being in a hospital for select MDCs. For the full sample I find a 1.3 percentage point increase in the likelihood of a discharge being for MDC 19: Mental Diseases and Disorders. I find a 0.6 percentage point increase in the likelihood of a discharge being for MDC 21: Injuries, Poison and Toxic Effect of Drugs. For both sexes I find increases in the likelihood of a discharge being for MDC 19. For females I find a 0.7 percentage point decrease in the likelihood of a discharge being for MDC 20: Alcohol/Drug Use or Induced Mental Disorders. For males I find a 0.7 percentage point decrease in the likelihood of a discharge being for MDC 21.

Table 3.6: Select Major Diagnosis Categories

	Panel A. full sample		
	MDC 19	MDC 20	MDC 21
Baseline model	0.0143***	0.0073	-0.0076***
	(0.0025)	(0.0050)	(0.0015)
+Risk controls†	0.0129***	0.0075	-0.0055**
	(0.0022)	(0.0051)	(0.0021)
Mean	0.1480	0.0474	0.0507
Sample Size	1,313,879	1,313,879	,1313,879
	Panel B. female sample		
	MDC 19	MDC 20	MDC 21
Baseline model	0.0151***	0.0063	-0.0062**
	(0.0024)	(0.0033)	(0.0023)
+Risk controls†	0.0145***	0.0069*	-0.0042
	(0.0025)	(0.0035)	(0.0028)
Mean	0.1439	0.0325	0.0458
Sample Size	663,121	663,121	663,121
	Panel B. male sample		
	MDC 19	MDC 20	MDC 21
Baseline model	0.0125**	0.0078	-0.0089***
	(0.0037)	(0.0070)	(0.0016)
+Risk controls†	0.0107**	0.0081	-0.0066**
	(0.0032)	(0.0072)	(0.0020)
Mean	0.1520	0.0625	0.0558
Sample Size	650,758	650,758	650,758

Notes: Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

†Controls for MDC are omitted.

3.4.2 Non-neonatal and Non-maternal Inpatient Mental Health Visits

In Table 3.7, I present the effects on primary payment source for mental health discharges. For the full sample, I find a 2.1 percentage point increase in the likelihood of the primary source of payment being some form of insurance. The gain in insurance is from a 1.8 percentage point increase in the likelihood of paying with private insurance and a 2.8 percentage point decrease in the likelihood of self-pay. For females I find a 1.2 percentage point increase in the likelihood of paying with insurance and a 1.8 percentage point decrease in the likelihood of self-pay. For males I find a 3.0 percentage point increase in the likelihood of paying with insurance and a 3.5 percentage point decrease in the likelihood of self-pay.

Table 3.7: Mental Health Admissions: Primary Payment Source

	Any insurance	Private insurance	Medicaid	Medicare	Self-pay
	Panel A. full sample				
	Any insurance	Private insurance	Medicaid	Medicare	Self-pay
Baseline model	0.0237***	0.0315***	-0.0013	-0.0066	-0.0311***
	(0.0052)	(0.0073)	(0.0121)	(0.0041)	(0.0036)
+Risk controls†	0.0210**	0.0182**	0.0052	-0.0024	-0.0279***
	(0.0068)	(0.0057)	(0.0119)	(0.0040)	(0.0052)
Mean	0.7738	0.3044	0.3683	0.1011	0.1782
Sample Size	194,201	194,201	194,201	194,201	194,201
	Panel B. female sample				
	Any insurance	Private insurance	Medicaid	Medicare	Self-pay
Baseline model	0.0109*	0.0172	0.0060	-0.0123	-0.0177***
	(0.0052)	(0.0094)	(0.0165)	(0.0084)	(0.0045)
+Risk controls†	0.0122**	0.0044	0.0151	-0.0072	-0.0177***
	(0.0046)	(0.0082)	(0.0139)	(0.0091)	(0.0034)
Mean	0.8118	0.3467	0.3855	0.0796	0.1405
Sample Size	95,344	95,344	95,344	95,344	95,344
	Panel C. male sample				
	Any insurance	Private insurance	Medicaid	Medicare	Self-pay
Baseline model	0.0336**	0.0425***	-0.0106	0.0017	-0.0405***
	(0.0123)	(0.0077)	(0.0121)	(0.0062)	(0.0087)
+Risk controls†	0.0.0277	0.0295***	-0.0066	0.0048	-0.0348**
	(0.0144)	(0.0058)	(0.0136)	(0.0064)	(0.0117)
Mean	0.7372	0.2635	0.3518	0.1219	0.2146
Sample Size	98,857	98,857	98,857	98,857	98,857

Notes: The sample is restricted to discharges with MDC 19. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

†Controls for MDC are omitted.

In Table 3.8, I present the effects on the characteristics of mental health inpatient discharges. The only effects I find are an increase in the number or procedures for the full sample and the male sample. Overall, there are are 0.015 more procedures performed and, for males, 0.017 more procedures performed.

Table 3.8: Mental Health Admissions: Characteristics of Inpatient Discharges

	Panel A. full sample			
	Length of stay	Log length of stay	Number of Procedures	Days until first procedure
Baseline model	-0.0384	0.0096	0.0097	-0.1212
	(0.1074)	(0.0103)	(0.006)	(0.3508)
+Risk controls†	0.0161	0.0166	0.0150**	-0.1319
	(0.1170)	(0.0120)	(0.0054)	(0.3370)
Mean	6.7656	1.5568	0.1966	1.3015
Sample Size	194,370	189,552	194,391	14,048
	Panel B. female sample			
	Length of stay	Log length of stay	Number of Procedures	Days until first procedure
Baseline model	-0.1578	0.0059	0.0045	-0.5474
	(0.1403)	(0.0187)	(0.0138)	(0.6126)
+Risk controls†	-0.0699	0.0189	0.0117	-0.5866
	(0.1323)	(0.0193)	(0.0129)	(0.6130)
Mean	6.7063	1.5313	0.1931	1.5774
Sample Size	95,436	93,011	95,450	6,453
	Panel B. male sample			
	Length of stay	Log length of stay	Number of Procedures	Days until first procedure
Baseline model	0.0120	0.0061	0.0136***	0.0965
	(0.1111)	(0.0133)	(0.0032)	(0.1951)
+Risk controls†	0.0411	0.0079	0.0174***	0.0879
	(0.1248)	(0.0146)	(0.0037)	(0.2046)
Mean	6.8228	1.5813	0.2000	1.0671
Sample Size	98,934	96,541	98,941	7,595

Notes: The sample is restricted to discharges with MDC 19. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

†Controls for MDC are omitted.

In Table 3.9, I look at the disposition at discharge among mental health discharges. For the full sample and for females I find no significant effects. For males I find an increase of 0.2 percentage points in the likelihood of being discharged to home health care.

Table 3.9: Mental Health Admissions: Patient's Disposition at Discharge

	Panel A. full sample			
	Routine	Hospital transfer	Home health care	Against medical advice
Baseline model	0.0044	-0.0005	0.0013	-0.0013
	(0.0054)	(0.0010)	(0.0008)	(0.0015)
+Risk controls†	0.0011	-0.0000	0.0014	-0.0010
	(0.0053)	(0.0011)	(0.0008)	(0.0017)
Mean	0.8692	0.0160	0.0028	0.0306
Sample Size	194,391	194,391	194,391	194,391
	Panel B. female sample			
	Routine	Hospital transfer	Home health care	Against medical advice
Baseline model	0.0004	0.0011	0.0007	-0.0003
	(0.0092)	(0.0013)	(0.0008)	(0.0017)
+Risk controls†	-0.0023	0.0013	0.0008	0.0001
	(0.0085)	(0.0013)	(0.0008)	(0.0019)
Mean	0.8899	0.0153	0.0029	0.0281
Sample Size	95,450	95,450	95,450	95,450
	Panel B. male sample			
	Routine	Hospital transfer	Home health care	Against medical advice
Baseline model	0.0072	-0.0015	0.0019*	-0.0021
	(0.0069)	(0.0013)	(0.0010)	(0.0025)
+Risk controls†	0.0035	-0.0009	0.0020*	-0.0019
	(0.0063)	(0.0017)	(0.0009)	(0.0027)
Mean	0.8492	0.0166	0.0027	0.0330
Sample Size	98,941	98,941	98,941	98,941

Notes: The sample is restricted to discharges with MDC 19. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

†Controls for MDC are omitted.

In Table 3.10, I present the effects on charges for mental health discharges. I find no effects on total charges or the log of total charges for the full sample, females or males.

Table 3.10: Mental Health Admissions: Charges

	Panel A. full sample	
	Total charges	Log total charges
Baseline model	-110.2589	0.0055
	(118.1450)	(0.0103)
+Risk controls†	-52.1260	0.0151
	(121.4329)	(0.0109)
Mean	4882.866	8.1545
Sample Size	194,032	194,032
	Panel B. female sample	
	Total charges	Log total charges
Baseline model	-228.7693	0.0016
	(173.1479)	(0.0133)
+Risk controls†	-149.3375	0.0175
	(166.0094)	(0.0136)
Mean	4842.026	8.1353
Sample Size	95,219	95,219
	Panel B. male sample	
	Total charges	Log total charges
Baseline model	-46.5088	0.0012
	(95.0582)	(0.0124)
+Risk controls†	-4.0327	0.0053
	(101.8722)	(0.0129)
Mean	4922.22	8.1730
Sample Size	98,813	98,813

Notes: Values are reported in 1988 USD. The sample is restricted to discharges with MDC 19. Standard errors clustered by state are presented in parentheses. Significance levels of 0.10, 0.05, and 0.01 are denoted by *, **, and ***, respectively.

†Controls for MDC are omitted.

3.5 Discussion and Conclusion

In this chapter I provide the first evidence of the effects state dependent mandates have on inpatient care. For the non-neonatal and non-maternal inpatient discharges, I find several changes in the primary source of payment among eligible individuals. For the full sample I find that they are more likely to pay with some form of insurance, largely attributed to a gain in private insurance and a decrease in the likelihood of self-pay. Looking by sex I find heterogeneous effects consistent with my findings in Chapter 2. The gains in any insurance were large and significant for males and smaller and insignificant for females. Similarly, the gains in private insurance were both bigger in magnitude and relative to the mean for males compared to females. For males the decrease in the likelihood of self-pay is more than double that for females. However, when looking at females I find decreases in public insurance which supports crowding in as they move to stay on their parents' private plan.

Looking at the characteristics of inpatient discharges I find results that are consistent with increased insurance coverage. With insurance or with a more generous plan a patient's cost of care is considerably lower. As expected with lower costs the eligible young adults—overall and by sex—have a longer stay and more procedures performed. Among the sexes the increases are similar in size, which is of note since only males have a gain in overall insurance coverage. Both females and males have similar absolute gains in private insurance coverage which combined with this result suggests that private insurance, rather than any insurance coverage, is an important determinant of the length of stay and number procedures for a young adult. Overall and by sex, I find that the amount of time until the first procedure increased. This could be due to several reasons. With insurance there may be increased bureaucratic measures required for non-urgent or optional procedures. Additionally with insurance the staff and patient may be less incentivized to minimize the length of stay and costs incurred. If there are additional procedures or tests that are suggested by the doctor but up to the patient's discretion or consent than gains in insurance could lower the costs enough that more patients agree to the additional procedures.

Looking at the patient's disposition at discharge I find some effects that are again consistent with the insured facing a lower cost of. Overall and by sex, I find an increase in the likelihood of being transfered to another hospital. An eligible young adult faces a lower cost for additional care or transferring to another treatment facility following dependent mandates. For females, I find a decrease in the likelihood of a routine discharge. For males, I find a decrease in the likelihood of them leaving against medical advice. There is no effect on the likelihood of leaving against medical advice for females. This could be attributed to the large gains in insurance coverage for males removing a sizable portion of the financial burden making them less likely to elect an early discharge despite a doctor recommending otherwise.

Turning to the total charges for the stay I find an increase in total charges and log total charges. This is consistent with the findings of an increase in procedures performed and length of stay. For each sex I find an increase in the log total charges but I only find an increase in total charges for the male sample. The average discharge for a young adult costs over $8,000. The decrease in young adults having a primary source of payment as self-pay could prevent a hospitalization form being a large negative financial shock.

I look for changes in the likelihood of a discharge being for a selection of MDCs. Overall and by sex, I find an increase in the likelihood of a discharge for MDC 19: mental diseases and disorders. This is consistent with Antwi et al. (2015) and Fronstin (2013) who find evidence that the ACA dependent mandate let to an increase of mental health inpatient discharges and mental health related claims. For the overall sample and for males I find a decrease in the likelihood of a discharge being for MDC 21: injuries, poison and toxic effect of drugs. For females, I find an increase in the likelihood of a discharge being for MDC 20: alcohol/drug use or induced mental disorders.

When I look at the effects on for the non-neonatal and non-maternal mental health inpatient discharges, I find similar effects for the primary source of payment and very little other effects. Overall and for females there is an increase in the primary source of payment being insurance. Overall and for males I find an increase in the likelihood that the primary source of payment is private insurance. Again, for both sexes and overall, I find a decrease in the likelihood of self-pay.

Beyond the primary source of payment there are few effects on this group. Overall and for males, there is an increase in the number of procedures. For males, there is an increase in the likelihood of being discharged to home health care. I find no effects on the total charges for the mental health group.

There are several weaknesses in my analysis. The NIS sample is not state representative so I am unable to infer how the total admissions have changed. Rather, I am limited to looking at how the composition of admissions changed, relying on the DDD framework and hospital fixed effects to account for any hospital or service area specific differences. Additionally, the NIS does not include psychiatric hospitals or alcoholism and chemical dependency facilities. Information on psychiatric hospital admissions would be useful in fully understanding how dependent mandates affect mental health care among young adults. There could be an increase in care for alcohol or drug use through alcoholism and chemical dependency facilities that would not be captured in this dataset. Future work looking at psychiatric hospital or alcoholism and dependency facilities would be helpful in shedding light on the overall mental health and substance abuse effects of dependent mandates.

Despite the limitation of my analysis, my analyses contribute to the literature on the effect of dependent mandates on medical care utilization. I provide the first evidence that state dependent mandates affected inpatient care among young adults. My findings are consistent with increased use of care following a gain in health insurance. My results differ from those of Antwi et al. (2015) who find no increases in the intensity of care as measured by the length of stay, number of procedures and total charges; for each measure of intensity of care I find evidence of an increase. Additionally, I find evidence supporting the increase in mental health care consumption among young adults who gain insurance through a dependent mandate.

Chapter 4

The Affordable Care Act Dependent Mandate and HIV Testing

4.1 Introduction

In the United States during 2015 there were 39,513 new diagnoses of HIV and one out of eight individuals living with HIV are unaware of their seropositive status (Centers for Disease Control and Prevention, 2016a). Looking at young adults under the age of twenty four, they account for over a fifth of all new transmissions in 2014 and half of young adults living with HIV are unaware of their seropositive status (Centers for Disease Control and Prevention, 2016a). Individuals who are unaware of their seropositive status are responsible for roughly half of all new transmissions (Hall et al., 2012). The important preventative role of knowing one's seropositive status has been emphasized through recent policy recommendations encouraging routine screening of all individuals.[1] Routine testing is of particular importance for young adults. Young adults have high rates of sexually transmitted infection (STI) relative to older individuals, accounting for nearly one half to two thirds of new STI diagnoses annually despite being a small percent of the sexually active population (Centers for Disease Control and Prevention, 2016b). HIV testing rates among young adults are important for several reasons unique to their age group: young adults are less concerned about the spread of HIV (Kaiser Family Foundation, 2012), have a lack of HIV-related education and have low condom-use rates (Centers for Disease Control and Prevention, 2016b).

Despite the important role of HIV testing in preventing the transmission of and beginning treatment for HIV, very little research has been done on insurance coverage and HIV testing. Using Medicaid eligibility and firm size to instrument for insurance coverage, Sood et al. (2015) find that insurance coverage increases HIV testing rates by 1.8 to 2.6 percentage points for low risk

[1] Routine screening is recommended by the Centers for Disease Control (CDC), the Infectious Diseases Society of America, the American Congress of Obstetricians and Gynecologists, and the United States Preventive Services Task Force (USPTF)

individuals and by 2.7 to 4.8 percentage points for high risk individuals.[2] In order to provide further evidence of the relationship between insurance coverage and HIV testing, I exploit the Affordable Care Act (ACA)'s dependent mandate which went into effect September 23, 2010. The mandate extended dependent insurance eligibility for adult children up to the age of twenty six. The ACA mandate has been successful in increasing insurance rates among young adults.[3] I provide the first evidence that the increase in coverage among young adults under the ACA dependent mandate resulted in an increased use of HIV screening services.

4.2 Methods

I aim to identify the effect of the ACA dependent mandate on HIV testing rates among the targeted young adults. To estimate the effect I use a differences-in-differences (DD) approach comparing the targeted individuals to a group of individuals just above the age cut off to qualify for dependent coverage under the ACA dependent mandate. Specifically I compare 23-25 year olds to 27-29 year olds.[4] Those aged 26 are excluded because it is unclear whether or not they have been treated. The estimating equation is given by

$$Y_{iast} = \alpha + \beta(PostExt_t \times Eligible_a) + \gamma X_i + \sigma Z_{st} + \nu_s + \delta_t + \varepsilon_{iast} \tag{4.1}$$

Where Y_{iast} is the outcome of interest for individual i of age a at year t living in state s. $PostExt_t$ is a dummy variable taking a value of one if the date of interview falls after September 23, 2010, when the dependent mandate took effect. $Eligible_a$ is a dummy variable taking a value of one if the individual's age is between 19-25. X_i is a vector of individual level controls for sex, race/ethnicity, marital status, education, income, number of household children, if the survey was done by cell phone, student status, unemployment status and pregnancy status. Z_{st} controls for state-level HIV testing policies and insurance mandates. State and year-month fixed effects—ν_s and δ_t—are in-

[2] High or low risk is based on what the respondent believes to be his or her own risk to contract HIV.

[3] Barbaresco et al. (2015), Sommers and Kronick (2012b), Sommers et al. (2012), Cantor et al. (2012b), Mulcahy et al. (2013b), and Antwi et al. (2015) document gains in insurance coverage.

[4] This approach has been widely used in works studying the ACA dependent mandate.

cluded. Additional analysis will be conducted using a limited number of fixed effects to test the sensitivity of the model. Standard errors are clustered at the state level.

4.3 Data and Variables

The primary data source used in this analysis is the Behavioral Risk Factor Surveillance System (BRFSS) from 2007 to 2014, which covers the period before and after when the ACA dependent mandate went into effect in September 2010. Administered by state health departments with assistance from the CDC, BRFSS is the largest continuous health survey in the U.S. and collects data by telephone survey fro over 400,000 adults in all 50 states each year. Each state survey contains a standard core set of questions with optional modules added by states' volition. A non-proxy telephone interview is conducted monthly among randomly selected adults eighteen years of age or older living in a household in the United States. BRFSS data includes several quality checks, including at least a five-percent random call-back policy to verify responses each month.[5] The BRFSS survey is well-suited for my analysis for several reasons. First, the core section contains standardized HIV questions asked to all respondents in each year. Second, it contains a large number of questions regarding an individual's demographic and household characteristics. Third, it contains state identifiers and is state representative—allowing me to control for relevant state policies. Fourth, it contains a very large sample size relative to other surveys which contain questions on HIV testing.

The introduction of cell phone data in 2011 raises concerns about the comparability of data before and after. With the addition of cell phone data the weighting methodology was changed as well. The changes may lead to certain state prevalence trends to shift upward but may not affect the shape or slop of the trend line (Pierannunzi et al., 2012). I address this in two ways. First I estimate equation 4.1 including an indicator variable if the survey was completed by cell phone and use the final weights for the period before and after 2011. The benefit of this approach is that I include the cell phone data but a potential problem arises if the cell phone data outcomes of the

[5] The verification may be omitted if the state utilizes electronic monitoring of interviewers.

younger age group differs drastically from the older age group. Second, I estimate equation 4.1 using only the landline data for the years 2011 onward and the corresponding landline weights. The advantage to this approach is that the weighting methods and survey methods are consistent. However, the drawback is that sample sizes will be lower since cell phone data is being ignored.

4.3.1 Dependent Variables

The BRFSS HIV questions allow me to create several measures of HIV testing among survey respondents. In the years included in my analysis, respondents were asked, “Have you ever been tested for HIV? Do not count tests you may have had as a part of a blood donation. Include testing fluid from your mouth.” From this question I define the outcome “Ever Had HIV Test” as equal to one if an individual has responded “yes” to this question and zero otherwise. The survey also asks, “Where did you have your last HIV test—at a private doctor or HMO office, at a counseling and testing site, in the emergency room, as an inpatient in a hospital, at a clinic, in a jail or prison, at a drug treatment facility, at home, or somewhere else?” In order to understand how the dependent mandate’s gain of insurance coverage affects the way treated individuals are tested, I create dummy variables for each of these test locations.

4.3.2 Independent Variables

I include the following individual characteristics as controls: age, sex, race/ethnicity, marital status, education, household income, number of children in household, student status, pregnancy status and unemployment status. I exclude any measure of health insurance since the change in health insurance is endogenous and may play a role in the mechanism through which individuals increase testing.

Table 4.1: Descriptive Statistics for Independent Variables

	Before 9/23/2010		After 9/23/2010	
	Ages 23-25	Ages 27-29	Ages 23-25	Ages 27-29
Female	0.503	0.506	0.483	0.480
Non-Hispanic black	0.111	0.114	0.133	0.128
Non-Hispanic, non-black, non-white	0.095	0.085	0.102	0.096
Hispanic	0.232	0.224	0.219	0.220
Married	0.289	0.550	0.184	0.383
High school degree or equivalent	0.290	0.261	0.269	0.245
Some college, but no bachelor degree	0.296	0.266	0.336	0.311
Bachelor degree or graduate degree	0.291	0.353	0.268	0.299
$10,000-$15,000	0.060	0.046	0.067	0.053
$15,000-$20,000	0.090	0.071	0.101	0.088
$20,000-$25,000	0.101	0.090	0.114	0.103
$25,000-$35,000	0.125	0.116	0.125	0.116
$35,000-$50,000	0.143	0.149	0.125	0.138
$50,000-$75,000	0.121	0.169	0.102	0.144
$75,000+	0.158	0.215	0.121	0.181
One child	0.228	0.231	0.195	0.199
Two children	0.154	0.228	0.119	0.180
Three children	0.054	0.108	0.045	0.090
Four children	0.019	0.037	0.014	0.031
Five or more children	0.008	0.015	0.007	0.013
Cell phone only			0.686	0.661
Pregnant	0.034	0.040	0.027	0.030
Student	0.114	0.053	0.077	0.034
Unemployed	0.118	0.099	0.075	0.064

Notes: All results reported use all data and BRFSS final weights. Cell phone data was introduced in 2011.

Table 4.1 presents the independent variables' descriptive statistics for the treatment and control groups before and after the ACA dependent mandate went into effect. The sample is nearly evenly split between male and female. For both groups, the majority of the sample are non-Hispanic whites, with blacks making up slightly more than ten percent, and Hispanics making up slightly more than twenty percent. There are some differences between the groups worth noting, most of which are expected due to the control group being older. First, the treated group is on average more likely to have some college but less likely to have completed a bachelor or higher degree. Second, the treated group is more likely to still be a student, which would partly explain the lower obtainment of a bachelor degree or higher. Third, the treated group is nearly half as likely to be married than the control group both before and after the ACA dependent mandate went into effect and marriage rates among both groups are lower in the period following the implementation of the ACA dependent mandate. The treated group is more likely to be among the lower income categories, with the distribution of income being fairly close between the two groups both before and after the ACA dependent mandate. Lastly the treated group is less likely to have children than the control group and, amongst those that do have children, they are less likely to have as many as the control group.

Table 4.2: Most Recent State Laws in Place Prior to ACA Dependent Mandate

State	Highest age eligible	Must be unmarried	Must be a student
Colorado	24	X	
Connecticut	25		
Delaware	23	X	
Florida	24		
Florida	29	X	X
Georgia	25		X
Idaho	24	X	
Illinois	25	X	
Indiana	23		
Iowa	24	X	X
Kentucky	24	X	
Louisiana	20	X	
Louisiana	23	X	X
Maine	24	X	
Maryland	24	X	
Massachusetts	25		
Minnesota	24	X	X
Missouri	25	X	
Montana	24	X	
Nevada	23	X	X
New Jersey	30	X	
New Mexico	24	X	
New York	29	X	
North Dakota	21		
North Dakota	25		X
Ohio	27	X	
Oregon	22	X	
Pennsylvania	29	X	
Rhode Island	24	X	
South Carolina	21	X	X
South Dakota	28		X
Tennessee	23		
Texas	24	X	
Utah	25	X	
Virginia	24		
Washington	24	X	
West Virginia	24	X	
Wyoming	22	X	X

For some additional analyses, I include state-specific controls for those that already had dependent mandates in place prior to the ACA being implemented. In Table 4.2, I present the age, marital and student eligibility requirements for state dependent mandates. A total of thirty five states had policies in place. Many states required individuals to be unmarried, students or some combination of the two in order to qualify as dependents on their parents' private plan.

Table 4.3: Descriptive Statistics for Policy Variables

	Before 9/23/2010		After 9/23/2010	
	Ages 23-25	Ages 27-29	Ages 23-25	Ages 27-29
Age eligible for state mandate	0.383	0.076	0.537	0.197
	(0.006)	(0.003)	(0.004)	(0.003)
Any consent laws	0.582	0.574	0.436	0.442
	(0.006)	(0.005)	(0.004)	(0.004)
Any opt-out laws	0.124	0.118	0.163	0.160
	(0.004)	(0.003)	(0.003)	(0.003)
Results must be informed	0.081	0.078	0.065	0.065
	(0.003)	(0.002)	(0.002)	(0.002)
Pre-test information	0.317	0.322	0.243	0.243
	(0.006)	(0.004)	(0.003)	(0.003)

Notes: All results reported use all data and BRFSS final weights.

Table 4.3 shows the proportion of the treated or control groups that are eligible for state dependent mandates or bound by state HIV testing before and after the ACA dependent mandate went into effect. Before the ACA dependent mandate, thirty-eight percent of the control group and about eight percent of the treatment group were eligible by age for a state-dependent mandate. After the ACA dependent mandate, these numbers rise to nearly fifty-four percent and twenty-percent, respectively. The higher percentage reflects the fact that several of the states had more stringent laws in place prior to the ACA dependent mandate and gradually moved toward less stringent laws before its implementation.

I include additional controls to account for state-level and year-level differences among respondents. First, I add a control for the states' annual unemployment level. Second, I include state and year-month fixed effects to account for any unobserved time invariant factors within a state and any national year-month specific unobservable factors. Third, I include dummy variables for state policies regarding HIV testing. Specifically, I control for state HIV policies on consent laws, opt out testing, requirements to inform patients of test results, and requirements to provide information prior to testing. The proportion bound by each of these state HIV testing policies is similar for the treatment and control groups in the years prior to and the years after the dependent mandate went into effect.

4.4 Results

4.4.1 HIV Testing

Table 4.4: Descriptive Statistics HIV Test Ever

	Before 9/23/2010		After 9/23/2010	
	Ages 23-25	Ages 27-29	Ages 23-25	Ages 27-29
All data	0.421	0.508	0.420	0.485
	(0.006)	(0.005)	(0.004)	(0.004)
Landline data only	0.421	0.508	0.402	0.483
	(0.006)	(0.005)	(0.008)	(0.007)

Notes: The results using all data use the BRFSS provided final weights. The landline only data uses the landline data and landline weights.

In Table 4.4, I present the descriptive statistics for the likelihood of having an HIV test ever for individuals in the treatment and control group for before and after the ACA dependent mandate. Roughly fifty percent of the 27-29 year olds have ever had an HIV test, with a small decline following the reform. About forty-two percent of the 23-25 year olds have ever had an HIV test in both periods.

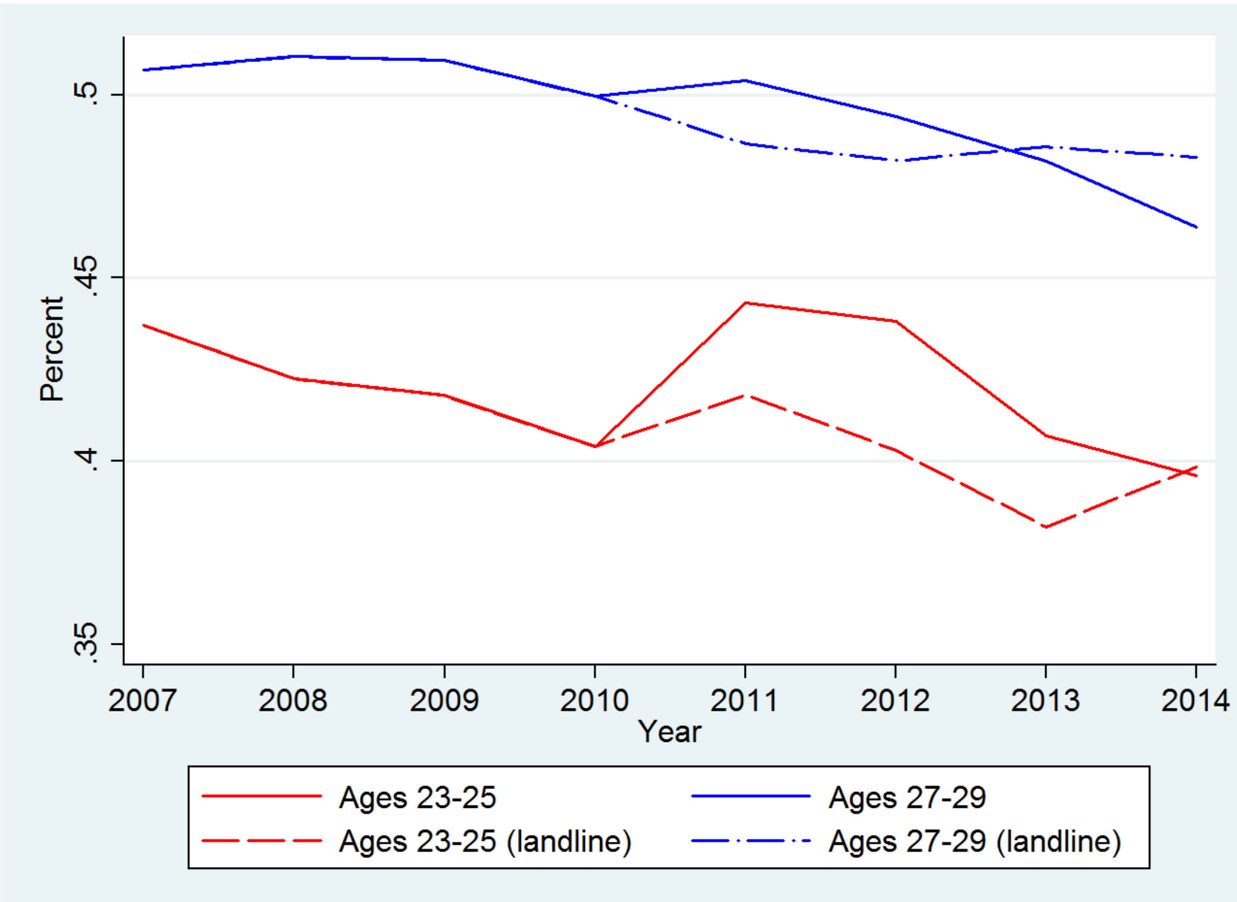


Figure 4.1: Percent Ever Tested for HIV by Group

Figure 4.1 shows the percent of the control and treatment groups who have reported ever having an HIV test by year. Using all data, both groups have an initial increase followed by a decline in the years before the reform and a decline which continues after the reform. The control group experiences a small increase following the reform, while the treatment group has a large increase. When only the landline data is used there is no increase for the control group following the reform but still a noticeable increase for the treated group.

Table 4.5: DD Estimates on the Likelihood of Ever Having an HIV Test

	1	2	3	4	5
All data	-0.005	0.021***	0.021***	0.021**	0.021**
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Sample size	166,677	166,677	166,677	166,677	166,677
Landline data	-0.019***	0.011*	0.011*	0.011*	0.011*
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Sample size	101,879	101,879	101,879	101,879	101,879
State fixed effects	X	X	X	X	X
Year-month fixed effects		X	X	X	X
State HIV laws			X		X
State dependent laws				X	X

Notes: The results using all data use the BRFSS provided final weights. The landline only data uses the landline data and landline weights.

In Table 4.5, I present the estimated effect of the ACA dependent mandate on HIV testing rates. Each estimate in the table includes state fixed effects, with other fixed effects being included as specified. First I present the results using all data. In the absence of year-month fixed effects, state HIV Laws and state dependent laws, there is an insignificant and small negatively signed result. When year-month fixed effects, there is a 2.1 percentage point increase in individuals ever having an HIV test. This estimate is robust when controlling for state HIV laws, state dependent laws, and the combination of the two. Next, I present the results using landline data only. Again I find a negative—albeit significant—decrease in testing rates when I exclude year-month fixed effects, state HIV laws and state dependent laws. When year-month fixed effects are included I find a 1.1 percentage point increase in the likelihood of treated individuals ever having taken an HIV test.

This estimate is robust to controls for state HIV laws and state dependent laws. Taken together this is strong evidence that the ACA dependent mandate increased the likelihood of treated respondents reporting ever had an HIV test outside of those conducted on blood donations by 2.6-5 percent of the pre-treatment mean.

4.4.2 Location of Last HIV Test

Table 4.6: Descriptive Statistics for Test Location

	Before 9/23/2010		After 9/23/2010	
	Ages 23-25	Ages 27-29	Ages 23-25	Ages 27-29
Private doctor or HMO	0.376	0.427	0.417	0.435
	(0.008)	(0.006)	(0.008)	(0.007)
Counseling and testing site	0.037	0.032	0.039	0.041
	(0.004)	(0.003)	(0.003)	(0.003)
Hospital†	0.140	0.152	0.092	0.085
	(0.006)	(0.005)	(0.005)	(0.004)
Clinic	0.322	0.262	0.293	0.296
	(0.008)	(0.006)	(0.007)	(0.007)
Jail, prison, or other correctional facility	0.020	0.020	0.014	0.019
	(0.003)	(0.002)	(0.002)	(0.002)
Drug treatment facility	0.006	0.006	0.010	0.007
	(0.001)	(0.001)	(0.002)	(0.001)
At home	0.010	0.020	0.007	0.011
	(0.002)	(0.002)	(0.001)	(0.001)

Notes: All results reported use all data and BRFSS final weights.

† *Hospital includes inpatient or emergency room. Initially the category was Hospital, but in 2013 and onward there were two separate categories: Hospital Inpatient and Emergency Room.*

Table 4.7: DD Estimates on the Likelihood of Test Location Among Those Tested

	Clinic	Private doctor or HMO	Hospital*	Counseling and testing site	Jail, prison, or other correctional facility	Drug treatment facility	At home	Somewhere else	Don't know
All data	-0.055***	0.021	0.022***	-0.004	-0.003	0.005**	0.004	0.011	0.002
	(0.012)	(0.017)	(0.005)	(0.008)	(0.004)	(0.002)	(0.002)	(0.010)	(0.003)
N=54701									
Landline data	-0.095**	0.049*	0.031***	-0.013	0.006	0.001	0.004***	0.010	0.014
	(0.024)	(0.023)	(0.007)	(0.007)	(0.005)	(0.005)	(0.001)	(0.017)	(0.010)
N=39543									

Notes: The results using all data use the BRFSS provided final weights. The landline only data uses the landline data and landline weights. DD estimates are reporting using specification (5) from Table 4.

In Table 4.6, I present the descriptive statistics for individuals in the treatment and control for before and after the ACA dependent mandate. The most common location of the last test for all groups is at a private doctor or HMO. The means of the control group are very close before and after the reform with the exception of a decrease in the likelihood of being last tested at a hospital.

Table 4.7 reports the DD estimates of the effect of the ACA dependent mandate on the location of the last HIV test while controlling for state fixed effects, year-month fixed effects, state HIV laws, and state dependent laws. I first present results using all data. Treated individuals are 5.5 percentage points less likely to have last been tested at a clinic, which is about seventeen percent of the pre-treatment mean. They were also 2.2 percentage points more likely to have the last test at a hospital which is about sixteen percent of the pre-treatment mean. Additionally, individuals were 0.5 percentage points more likely go have last been tested at a drug treatment facility which is sizable compared to the pre-treatment mean of 0.6 percent. Next I present results using the landline data only. I find a larger decrease in the likelihood of being tested at a clinic. I find a large increase in the likelihood of being tested at a hospital. I find no significant effect on the likelihood of being tested at a drug treatment facility. I do find evidence of increases in the last test being at home, or at a private doctor or HMO office.

4.5 Discussion and Conclusion

My findings provide evidence that the ACA dependent mandate increased the likelihood of treated respondents reporting ever having an HIV test outside of those conducted on blood donations. This result is also evidence that the ACA dependent mandate has had an impact on preventive care in the form of HIV testing. I also find that the ACA dependent mandate has had an effect on the location of individual's last HIV test, with the most notable changes being an increase in testing done at a hospital and a decrease in testing at clinics.

There are some limitations to my study. The result is indicative that the ACA dependent mandate induced more individuals to get their first-ever HIV test, but it does not allow me to determine if the individuals who already have been tested increased testing frequency or if the individuals who are tested change behavior following the test. I also am unable to determine the mechanism through which the ACA dependent mandate works to increase HIV testing rates. One plausible mechanism is that individuals who gain insurance get back into the health care system and are more likely to be hospitalized for procedures, or as a part of a new patient initial checkup, in which a doctor performs a wide variety of diagnostic tests, which may include drawing blood and testing for HIV antibodies. The gain of insurance could also increase HIV testing by lowering the cost by making the test cheaper and lowering the cost of seeing a physician. Insurance also decreases the costs of treating HIV in the case of a positive diagnosis.

In an attempt to provide some insight into the validity of various mechanisms, I examined the location of respondents' last HIV test. The change in location provides limited evidence, since it is merely a change in the composition of test location among all individuals who have ever been tested. I am unable to determine which of these individuals are those that were induced into having their first HIV test by the ACA dependent mandate. The increase in likelihood of being tested at a hospital and the limited evidence of an increase in testing at a doctor's office supports the hypothesis that the increase may work through lowering the cost of testing and through increased health care utilization. The decrease in likelihood of being tested at a clinic coupled with the increased likelihood of being tested after the reform suggests that individuals are being tested more but they are choosing to have tests done at locations other than a clinic. The benefits of this are unclear. It may be beneficial if the individual is having a test done through a physician which has spillover effects by virtue of the physician providing medical treatment and advice for aspects of their life outside of sexual health. It may, however, be harmful to sexual health if the clinic's staff provides more information about safe sexual practices and if the patient is more willing to talk to a sexual-health professional about sexual health than a primary care physician.

Despite these limitations, my results provide some of the first evidence that the ACA dependent mandate increased preventive screening and shows that insurance gains are associated with increased HIV testing among young adults. In order to further understand the exact mechanism through which individuals are induced to be tested and how the insurance gain affects individuals who already had been tested, additional research must be done.

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